Word Alignment

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CS159 – Spring 2023

Some slides adapted from

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UC Berkeley

1

Admin

Assignment 5

Assignment 6 out later today: due Sunday 11/13

2

Language translation

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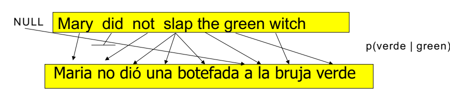
Word models: IBM Model 1



Each foreign word is aligned to exactly one English word

This is the **ONLY** thing we model!

$$p(f_1 f_2 \ldots f_{|F|}, a_1 a_2 \ldots a_{|F|} \mid e_1 e_2 \ldots e_{|E|}) = \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$$

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Training a word-level model

The old man is happy. He has fished many times.	El viejo está feliz porque ha pescado muchos veces.
His wife talks to him.	Su mujer habla con él.
The sharks await.	Los tiburones esperan.
…	…

$$p(f_1 f_2 \ldots f_{|F|}, a_1 a_2 \ldots a_{|F|} \mid e_1 e_2 \ldots e_{|E|}) = \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$$

$p(f_i \mid e_{a_i})$: probability that *e* is translated as *f*

How do we learn these?

What data would be useful?

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Thought experiment

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

His wife talks to him.

Su mujer habla con él.

The sharks await.

Los tiburones esperan.

$p(f_i \mid e_{a_i}) =$?

p(el | the) = ?
p(Los | the) = ?

6

Thought experiment

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

His wife talks to him.

Su mujer habla con él.

The sharks await.

Los tiburones esperan.

$$p(f_i \mid e_{a_i}) = \frac{count(f \text{ aligned-to } e)}{count(e)}$$

p(el | the) = 0.5
p(Los | the) = 0.5

Any problems concerns?

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Thought experiment

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

His wife talks to him.

Su mujer habla con él.

The sharks await.

Los tiburones esperan.

Getting data like this is expensive!

Even if we had it, what happens when we switch to a new domain/corpus

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Thought experiment #2

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

Annotator 1

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

Annotator 2

$$p(f_i | e_{a_i}) = \frac{count(f\ aligned\text{-}to\ e)}{count(e)}$$

What do we do?

9

Thought experiment #2

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

80 annotators

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

20 annotators

$$p(f_i | e_{a_i}) = \frac{count(f\ aligned\text{-}to\ e)}{count(e)}$$

What do we do?

10

Thought experiment #2

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

80 annotators

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

20 annotators

$$p(f_i | e_{a_i}) = \frac{count(f\ aligned\text{-}to\ e)}{count(e)}$$

Use partial counts:
- count(viejo ↔ man) 0.8
- count(viejo ↔ old) 0.2

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Training without alignments

a b

x y

How should these be aligned?

c b

z x

There is some information!
(Think of the alien translation task last time)

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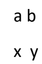
Training without alignments



IBM model 1: Each foreign word is aligned to 1 English word (ignore NULL for now)

What are the possible alignments?

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Training without alignments

IBM model 1: Each foreign word is aligned to 1 English word

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Training without alignments

0.01 0.9 0.08 0.01

IBM model 1: Each foreign word is aligned to 1 English word

If I told you how likely each of these were, does that help us with calculating p(f | e)?

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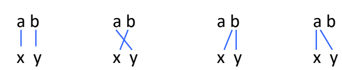
Training without alignments



0.01 0.9 0.08 0.01

IBM model 1: Each foreign word is aligned to 1 English word

$$p(f_i \mid e_{a_i}) = \frac{count(f \text{ aligned-to } e)}{count(e)}$$

Use partial counts and sum:
- count(y ↔ a) 0.9+0.01
- count(x ↔ a) 0.01+0.01

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One the one hand

0.01 0.9 0.08 0.01

If you had the likelihood of each alignment, you could calculate p(f|e)

$$p(f_i \mid e_{a_i}) = \frac{count(f \text{ aligned-to } e)}{count(e)}$$

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One the other hand

$$p(F, a_1 a_2 \ldots a_{|F|} \mid E) = \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$$

If you had p(f|e) could you calculate the probability of the alignments?

$p(f_i \mid e_{a_i})$

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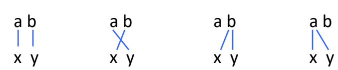
One the other hand



We want to calculate the probability of the alignment, e.g.

$$p(alignment1 \mid F, E) = p(A_1 \mid F, E)$$

We can calculate $p(A_1, F \mid E)$ using the word probabilities.

$$p(F, a_1 a_2 \ldots a_{|F|} \mid E) = \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$$

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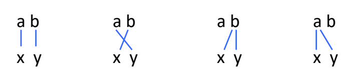
One the other hand



We want to calculate the probability of the alignment, e.g.

$$p(alignment1 \mid F, E) = p(A_1 \mid F, E)$$

We can calculate $p(A_1, F \mid E)$ using the word probabilities.

$p(A, F \mid E)$? $p(A \mid F, E)$

How are these two probabilities related?

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Our friend the chain rule

$p(A_1, F|E) = p(A_1|F, E) * p(F|E)$

$p(A_1|F, E) = \frac{p(A_1, F|E)}{P(F|E)}$

What is P(F|E)?

Hint: how do we go from p(A,F|E) to P(F|E)?

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Our friend the chain rule

$p(A_1, F|E) = p(A_1|F, E) * p(F|E)$

$p(A_1|F, E) = \frac{p(A_1, F|E)}{P(F|E)}$

$p(A_1|F, E) = \frac{p(A_1, F|E)}{\sum_A P(A, F|E)}$ sum over the variable!

How likely is this alignment,
compared to all other alignments
under the model

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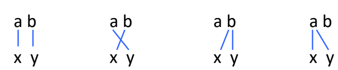
One the other hand

Alignment 1 Alignment 2 Alignment 3 Alignment 4



Alignment 1	Alignment 2	Alignment 3	Alignment 4
$p(x \mid a) * p(y \mid b)$	$p(x \mid b) * p(y \mid a)$	$p(x \mid b) * p(y \mid b)$	$p(x \mid a) * p(y \mid a)$
$p(F, a_1 \mid E)$	$p(F, a_2 \mid E)$	$p(F, a_3 \mid E)$	$p(F, a_4 \mid E)$

$$p(F, a_1 a_2 \ldots a_{|F|} \mid E) = \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$$

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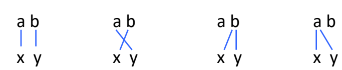
One the other hand

Alignment 1 Alignment 2 Alignment 3 Alignment 4



Alignment 1	Alignment 2	Alignment 3	Alignment 4
$p(x \mid a) * p(y \mid b)$	$p(x \mid b) * p(y \mid a)$	$p(x \mid b) * p(y \mid b)$	$p(x \mid a) * p(y \mid a)$
$p(F, a_1 \mid E)$	$p(F, a_2 \mid E)$	$p(F, a_3 \mid E)$	$p(F, a_4 \mid E)$

Normalize

$$p(a_1|E, F) = \frac{p(x|a) * p(y|b)}{\sum_{i=1}^{4} p(F, ai|E)}$$

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Have we gotten anywhere?

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Training without alignments

Initially assume a p(f|e) are equally probable

Repeat:

- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))
- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

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EM algorithm

(*something from nothing*)

General approach for calculating "hidden variables", i.e. variables without explicit labels in the data

Repeat:

E-step: Calculate the expected probabilities of the hidden variables based on the current model

M-step: Update the model based on the expected counts/probabilities

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EM alignment

E-step

- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step

- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

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green house

casa verde

the house

la casa

What are the different p(f|e) that make up my model?

p(casa | green)	
p(verde | green)	
p(la | green)	

p(casa | house)	
p(verde | house)	
p(la | house)	

p(casa | the)	
p(verde | the)	
p(la | the)	

Technically, all combinations of foreign and English words

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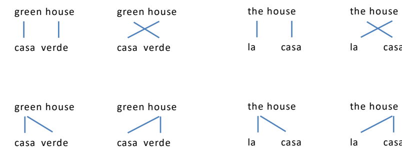

p(casa | green)	1/3
p(verde | green)	1/3
p(la | green)	1/3

p(casa | house)	1/3
p(verde | house)	1/3
p(la | house)	1/3

p(casa | the)	1/3
p(verde | the)	1/3
p(la | the)	1/3

Start with all p(f|e) equally probable

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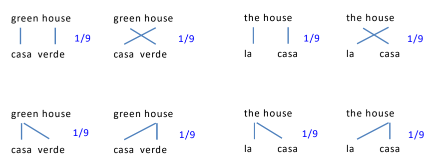

p(casa | green)	1/3
p(verde | green)	1/3
p(la | green)	1/3

p(casa | house)	1/3
p(verde | house)	1/3
p(la | house)	1/3

p(casa | the)	1/3
p(verde | the)	1/3
p(la | the)	1/3

E-step: What are the probabilities of the alignments?

1. calculate: $p(f_1 f_2 \ldots f_{|F|}, a_1 a_2 \ldots a_{|F|} \mid e_1 e_2 \ldots e_{|E|}) = \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$

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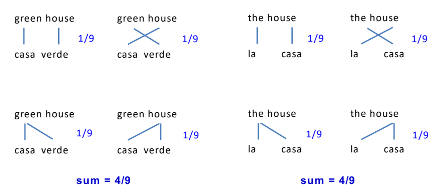

p(casa | green)	1/3
p(verde | green)	1/3
p(la | green)	1/3

p(casa | house)	1/3
p(verde | house)	1/3
p(la | house)	1/3

p(casa | the)	1/3
p(verde | the)	1/3
p(la | the)	1/3

E-step: What are the probabilities of the alignments?

2. normalize: $p(a_i|E,F) = \frac{p(F,ai|E)}{\sum_{j=1}^{4} p(F,aj|E)}$

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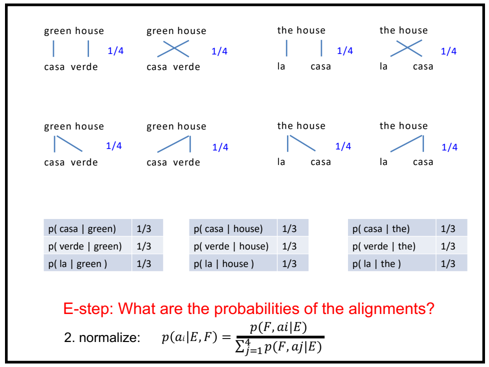
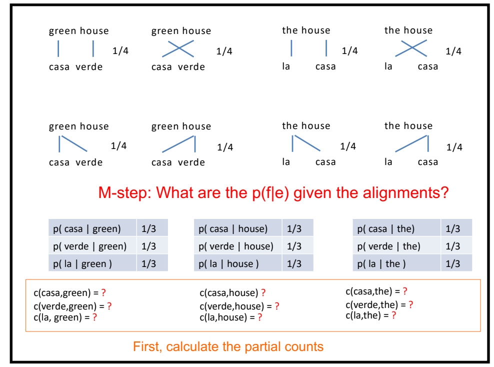

green house
1/4
casa verde
green house
1/4
casa verde
the house
1/4
la casa
the house
1/4
la casa
green house
1/4
casa verde
green house
1/4
casa verde
the house
1/4
la casa
the house
1/4
la casa
p(casa | green) 1/3
p(verde | green) 1/3
p(la | green) 1/3
p(casa | house) 1/3
p(verde | house) 1/3
p(la | house) 1/3
p(casa | the) 1/3
p(verde | the) 1/3
p(la | the) 1/3
E-step: What are the probabilities of the alignments?
2. normalize: $p(a_i|E,F) = \frac{p(F,ai|E)}{\sum_{j=1}^{4} p(F,aj|E)}$

33


green house
1/4
casa verde
green house
1/4
casa verde
the house
1/4
la casa
the house
1/4
la casa
green house
1/4
casa verde
green house
1/4
casa verde
the house
1/4
la casa
the house
1/4
la casa
M-step: What are the p(f|e) given the alignments?
p(casa | green) 1/3
p(verde | green) 1/3
p(la | green) 1/3
p(casa | house) 1/3
p(verde | house) 1/3
p(la | house) 1/3
p(casa | the) 1/3
p(verde | the) 1/3
p(la | the) 1/3
c(casa,green) = ?
c(verde,green) = ?
c(la, green) = ?
c(casa,house) ?
c(verde,house) = ?
c(la,house) = ?
c(casa,the) = ?
c(verde,the) = ?
c(la,the) = ?
First, calculate the partial counts

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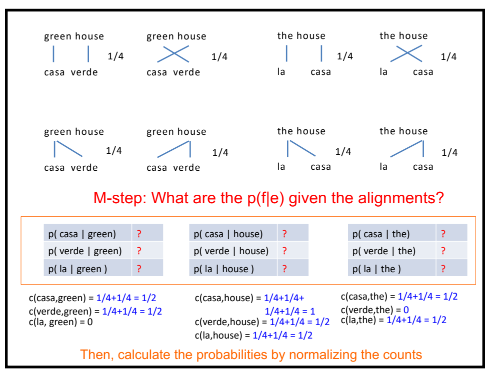
green house
1/4
casa verde
green house
1/4
casa verde
the house
1/4
la casa
the house
1/4
la casa
green house
1/4
casa verde
green house
1/4
casa verde
the house
1/4
la casa
the house
1/4
la casa
M-step: What are the p(f|e) given the alignments?
p(casa | green) ?
p(verde | green) ?
p(la | green) ?
p(casa | house) ?
p(verde | house) ?
p(la | house) ?
p(casa | the) ?
p(verde | the) ?
p(la | the) ?
c(casa,green) = 1/4+1/4 = 1/2
c(verde,green) = 1/4+1/4 = 1/2
c(la, green) = 0
c(casa,house) = 1/4+1/4+
1/4+1/4 = 1
c(verde,house) = 1/4+1/4 = 1/2
c(la,house) = 1/4+1/4 = 1/2
c(casa,the) = 1/4+1/4 = 1/2
c(verde,the) = 0
c(la,the) = 1/4+1/4 = 1/2
Then, calculate the probabilities by normalizing the counts

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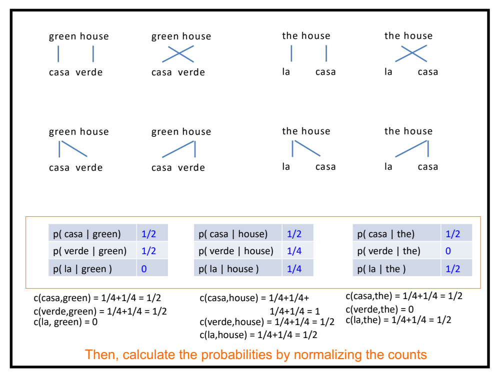
green house
casa verde
green house
casa verde
the house
la casa
the house
la casa
green house
casa verde
green house
casa verde
the house
la casa
the house
la casa
p(casa | green) 1/2
p(verde | green) 1/2
p(la | green) 0
p(casa | house) 1/2
p(verde | house) 1/4
p(la | house) 1/4
p(casa | the) 1/2
p(verde | the) 0
p(la | the) 1/2
c(casa,green) = 1/4+1/4 = 1/2
c(verde,green) = 1/4+1/4 = 1/2
c(la, green) = 0
c(casa,house) = 1/4+1/4+
1/4+1/4 = 1
c(verde,house) = 1/4+1/4 = 1/2
c(la,house) = 1/4+1/4 = 1/2
c(casa,the) = 1/4+1/4 = 1/2
c(verde,the) = 0
c(la,the) = 1/4+1/4 = 1/2
Then, calculate the probabilities by normalizing the counts

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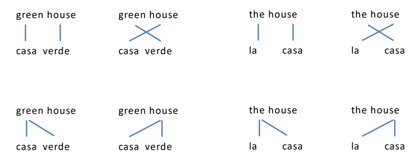

p(casa | green)	1/2	p(casa | house)	1/2	p(casa | the)	1/2
p(verde | green)	1/2	p(verde | house)	1/4	p(verde | the)	0
p(la | green)	0	p(la | house)	1/4	p(la | the)	1/2

E-step: 1. what are the p(A,F|E)?

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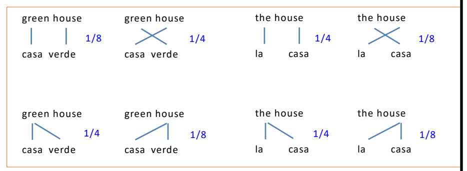

p(casa | green)	1/2	p(casa | house)	1/2	p(casa | the)	1/2
p(verde | green)	1/2	p(verde | house)	1/4	p(verde | the)	0
p(la | green)	0	p(la | house)	1/4	p(la | the)	1/2

E-step: 1. what are the p(A,F|E)?

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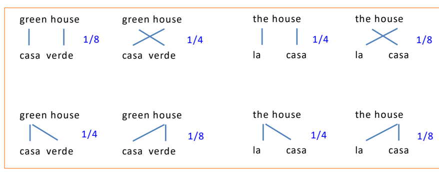

sum = (3/4) **sum = (3/4)**

p(casa | green)	1/2	p(casa | house)	1/2	p(casa | the)	1/2
p(verde | green)	1/2	p(verde | house)	1/4	p(verde | the)	0
p(la | green)	0	p(la | house)	1/4	p(la | the)	1/2

$$p(a_i|E,F) = \frac{p(F,ai|E)}{\sum_{j=1}^{4} p(F,aj|E)}$$

E-step: 2. what are the alignments, i.e. normalize?

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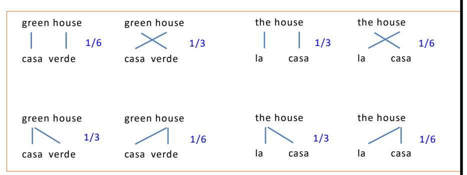


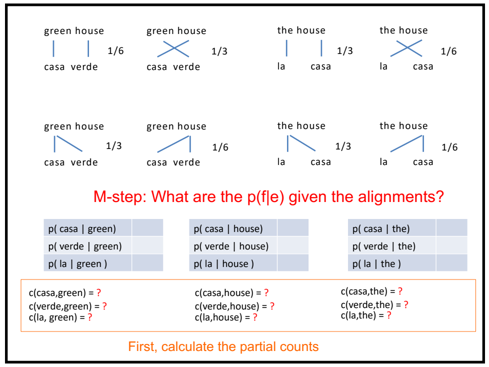
sum = (3/4) **sum = (3/4)**

p(casa | green)	1/2	p(casa | house)	1/2	p(casa | the)	1/2
p(verde | green)	1/2	p(verde | house)	1/4	p(verde | the)	0
p(la | green)	0	p(la | house)	1/4	p(la | the)	1/2

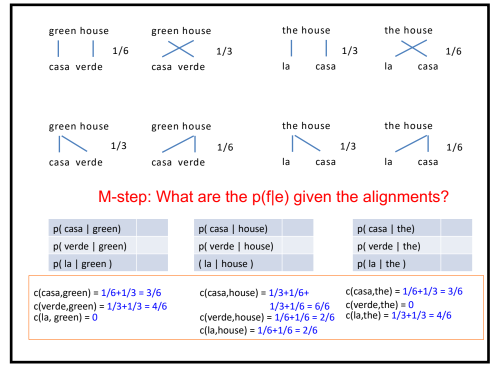
$$p(a_i|E,F) = \frac{p(F,ai|E)}{\sum_{j=1}^{4} p(F,aj|E)}$$

E-step: 2. what are the alignments, i.e. normalize?

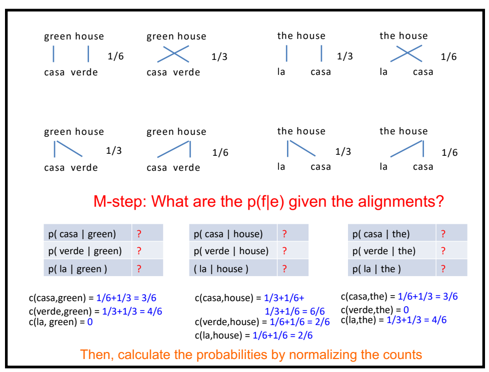
40


green house
1/6
casa verde
green house
1/3
casa verde
the house
1/3
la casa
the house
1/6
la casa
green house
1/3
casa verde
green house
1/6
casa verde
the house
1/3
la casa
the house
1/6
la casa
M-step: What are the p(f|e) given the alignments?
p(casa | green)
p(verde | green)
p(la | green)
p(casa | house)
p(verde | house)
p(la | house)
p(casa | the)
p(verde | the)
p(la | the)
c(casa,green) = ?
c(verde,green) = ?
c(la, green) = ?
c(casa,house) = ?
c(verde,house) = ?
c(la,house) = ?
c(casa,the) = ?
c(verde,the) = ?
c(la,the) = ?
First, calculate the partial counts

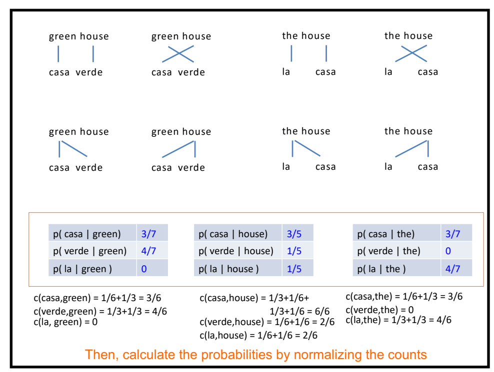
41


green house
1/6
casa verde
green house
1/3
casa verde
the house
1/3
la casa
the house
1/6
la casa
green house
1/3
casa verde
green house
1/6
casa verde
the house
1/3
la casa
the house
1/6
la casa
M-step: What are the p(f|e) given the alignments?
p(casa | green)
p(verde | green)
p(la | green)
p(casa | house)
p(verde | house)
(la | house)
p(casa | the)
p(verde | the)
p(la | the)
c(casa,green) = 1/6+1/3 = 3/6
c(verde,green) = 1/3+1/3 = 4/6
c(la, green) = 0
c(casa,house) = 1/3+1/6+
1/3+1/6 = 6/6
c(verde,house) = 1/6+1/6 = 2/6
c(la,house) = 1/6+1/6 = 2/6
c(casa,the) = 1/6+1/3 = 3/6
c(verde,the) = 0
c(la,the) = 1/3+1/3 = 4/6

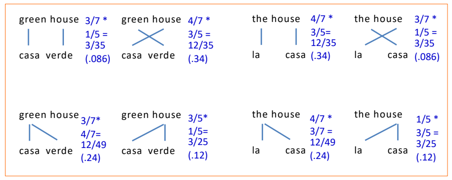
42


green house
1/6
casa verde
green house
1/3
casa verde
the house
1/3
la casa
the house
1/6
la casa
green house
1/3
casa verde
green house
1/6
casa verde
the house
1/3
la casa
the house
1/6
la casa
M-step: What are the p(f|e) given the alignments?
p(casa | green) ?
p(verde | green) ?
p(la | green) ?
p(casa | house) ?
p(verde | house) ?
(la | house) ?
p(casa | the) ?
p(verde | the) ?
p(la | the) ?
c(casa,green) = 1/6+1/3 = 3/6
c(verde,green) = 1/3+1/3 = 4/6
c(la, green) = 0
c(casa,house) = 1/3+1/6+
1/3+1/6 = 6/6
c(verde,house) = 1/6+1/6 = 2/6
c(la,house) = 1/6+1/6 = 2/6
c(casa,the) = 1/6+1/3 = 3/6
c(verde,the) = 0
c(la,the) = 1/3+1/3 = 4/6
Then, calculate the probabilities by normalizing the counts

43


green house
casa verde
green house
casa verde
the house
la casa
the house
la casa
green house
casa verde
green house
casa verde
the house
la casa
the house
la casa
p(casa | green) 3/7
p(verde | green) 4/7
p(la | green) 0
p(casa | house) 3/5
p(verde | house) 1/5
p(la | house) 1/5
p(casa | the) 3/7
p(verde | the) 0
p(la | the) 4/7
c(casa,green) = 1/6+1/3 = 3/6
c(verde,green) = 1/3+1/3 = 4/6
c(la, green) = 0
c(casa,house) = 1/3+1/6+
1/3+1/6 = 6/6
c(verde,house) = 1/6+1/6 = 2/6
c(la,house) = 1/6+1/6 = 2/6
c(casa,the) = 1/6+1/3 = 3/6
c(verde,the) = 0
c(la,the) = 1/3+1/3 = 4/6
Then, calculate the probabilities by normalizing the counts

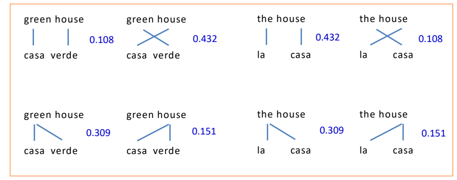
44



p(casa | green)	3/7	p(casa | house)	3/5	p(casa | the)	3/7
p(verde | green)	4/7	p(verde | house)	1/5	p(verde | the)	0
p(la | green)	0	p(la | house)	1/5	p(la | the)	4/7

E-step: 1. what are the p(A,F|E)?

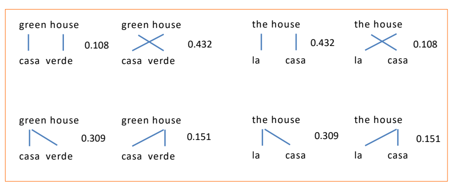
45



p(casa | green)	3/7	p(casa | house)	3/5	p(casa | the)	3/7
p(verde | green)	4/7	p(verde | house)	1/5	p(verde | the)	0
p(la | green)	0	p(la | house)	1/5	p(la | the)	4/7

E-step: 2. what are the alignments, i.e. normalize?

46



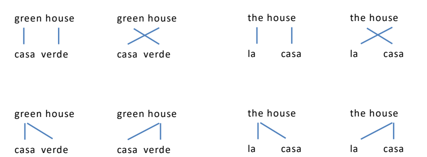
p(casa | green)	3/7	p(casa | house)	3/5	p(casa | the)	3/7
p(verde | green)	4/7	p(verde | house)	1/5	p(verde | the)	0
p(la | green)	0	p(la | house)	1/5	p(la | the)	4/7

c(casa,green) = .108+.309=0.417
c(verde,green) = .432+.309 = 0.741
c(la, green) = 0

c(casa,house) = .432+.151+ .432+.151=1.166
c(verde,house) = .108+.151=.259
c(la,house) = .108+.151=0.259

c(casa,the) = .108+.309=0.417
c(verde,the) = 0
c(la,the) = .432+.309=0.741

47



p(casa | green)	0.36	p(casa | house)	0.69	p(casa | the)	0.36
p(verde | green)	0.64	p(verde | house)	0.15	p(verde | the)	0
p(la | green)	0	p(la | house)	0.15	p(la | the)	0.64

c(casa,green) = .108+.309=0.417
c(verde,green) = .432+.309 = 0.741
c(la, green) = 0

c(casa,house) = .432+.151+ .432+.151=1.166
c(verde,house) = .108+.151=.259
c(la,house) = .108+.151=0.259

c(casa,the) = .108+.309=0.417
c(verde,the) = 0
c(la,the) = .432+.309=0.741

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Iterate…

5 iterations	
$p(casa \mid green)$	0.24
$p(verde \mid green)$	0.76
$p(la \mid green)$	0
$p(casa \mid house)$	0.84
$p(verde \mid house)$	0.08
$p(la \mid house)$	0.08
$p(casa \mid the)$	0.24
$p(verde \mid the)$	0
$p(la \mid the)$	0.76

10 iterations	
$p(casa \mid green)$	0.1
$p(verde \mid green)$	0.9
$p(la \mid green)$	0
$p(casa \mid house)$	0.98
$p(verde \mid house)$	0.01
$p(la \mid house)$	0.01
$p(casa \mid the)$	0.1
$p(verde \mid the)$	0
$p(la \mid the)$	0.9

100 iterations	
$p(casa \mid green)$	0.005
$p(verde \mid green)$	0.995
$p(la \mid green)$	0
$p(casa \mid house)$	~1.0
$p(verde \mid house)$	~0.0
$p(la \mid house)$	~0.0
$p(casa \mid the)$	0.005
$p(verde \mid the)$	0
$p(la \mid the)$	0.995

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EM alignment

E-step
- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step
- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

Why does it work?

50

EM alignment

E-ste
–
–


der the

M-st
–
ıents,

Why does it work?

51

EM alignment

Intuitively:

M-step
- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

Things that co-occur will have higher probabilities

E-step
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

Alignments that contain things with higher p(f|e) will be scored higher

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An aside: estimating probabilities

What is the probability of "the" occurring in a sentence?

$$\frac{\text{number of sentences with "the"}}{\text{total number of sentences}}$$

Is this right?

53

Estimating probabilities

What is the probability of "the" occurring in a sentence?

$$\frac{\text{number of sentences with "the"}}{\text{total number of sentences}}$$

No. This is an *estimate* based on our data

This is called the maximum likelihood estimation. Why?

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Maximum Likelihood Estimation (MLE)

Maximum likelihood estimation picks the values for the model parameters that maximize the likelihood of the training data

You flip a coin 100 times. 60 times you get heads.

What is the MLE for heads?

p(head) = 0.60

55

Maximum Likelihood Estimation (MLE)

Maximum likelihood estimation picks the values for the model parameters that maximize the likelihood of the training data

You flip a coin 100 times. 60 times you get heads.

What is the likelihood of the data under this model (each coin flip is a data point)?

56

MLE example

You flip a coin 100 times. 60 times you get heads.

MLE for heads: p(head) = 0.60

What is the likelihood of the data under this model (each coin flip is a data point)?

$$likelihood(data) = \prod_i p(x_i)$$

$\log(0.60^{60} * 0.40^{40}) = -67.3$

57

MLE example

Can we do any better?

$$likelihood(data) = \prod_i p(x_i)$$

p(heads) = 0.5

$\log(0.50^{60} * 0.50^{40}) = -69.3$

p(heads) = 0.7

– $\log(0.70^{60} * 0.30^{40}) = -69.5$

58

EM alignment: the math

The EM algorithm tries to find parameters of the model (p(f|e)) that *maximize the likelihood of the data*

In our case:

$$p(f_1 f_2 \ldots f_{|F|} \mid e_1 e_2 \ldots e_{|E|}) = \sum_{a_1} \sum_{a_2} \ldots \sum_{a_{|F|}} p(f_i \mid e_{a_i})$$

Each iteration, we increase (or keep the same) the likelihood of the data

59

Implementation details

Any concerns/issues?
Anything underspecified?

Repeat:

E-step
- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step
- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

60

Implementation details

When do we stop?

Repeat:

E-step

- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step

- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

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Implementation details

- Repeat for a fixed number of iterations
- Repeat until parameters don't change (much)
- Repeat until likelihood of data doesn't change much

Repeat:

E-step

- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step

- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

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Implementation details

For |E| English words and |F| foreign words, how many alignments are there?

Repeat:

E-step

- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step

- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

63

Implementation details

Each foreign word can be aligned to any of the English words (or NULL)

$(|E|+1)^{|F|}$

Repeat:

E-step

- Enumerate all possible alignments
- Calculate how probable the alignments are under the current model (i.e. p(f|e))

M-step

- Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

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Thought experiment

The old man is happy. He has fished many times.

El viejo está feliz porque ha pescado muchos veces.

His wife talks to him.

Su mujer habla con él.

The sharks await.

Los tiburones esperan.

$$p(f_i \mid e_{a_i}) = \frac{count(f \ aligned\text{-}to \ e)}{count(e)}$$

p(el ↔ the) = 0.5
p(Los ↔ the) = 0.5

65

If we had the alignments

Input: corpus of English/Foreign sentence pairs along with alignment

```
for (E, F) in corpus:
    for aligned words (e, f) in pair (E,F):
        count(e,f) += 1
        count(e) += 1

for all (e,f) in count:
    p(f|e) = count(e,f) / count(e)
```

66

If we had the alignments

Input: corpus of English/Foreign sentence pairs along with alignment

```
for (E, F) in corpus:
    for e in E:
        for f in F:
            if f aligned-to e:
                count(e,f) += 1
                count(e) += 1

for all (e,f) in count:
    p(f|e) = count(e,f) / count(e)
```

67

If we had the alignments

Input: corpus of English/Foreign sentence pairs along with alignment

```
for (E, F) in corpus:
    for aligned words (e, f) in pair (E,F):
        count(e,f) += 1
        count(e) += 1
```

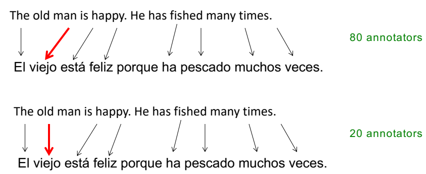
```
for (E, F) in corpus
    for e in E:
        for f in F:
            if f aligned-to e:
                count(e,f) += 1
                count(e) += 1
```

Are these equivalent?

```
for all (e,f) in count:
    p(f|e) = count(e,f) / count(e)
```

68

Thought experiment #2



$$p(f_i \mid e_{a_i}) = \frac{count(f\ aligned\text{-}to\ e)}{count(e)}$$

Use partial counts:
- count(viejo ↔ man) 0.8
- count(viejo ↔ old) 0.2

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Without the alignments

```
if f aligned-to e:
        count(e,f) += 1
        count(e) += 1
```

⬇

$p(f \rightarrow e)$: probability that f is aligned to e *in this pair*
count(e,f) += $p(f \rightarrow e)$
count(e) += $p(f \rightarrow e)$

Key: use ***expected*** counts (i.e., how likely based on the current model), rather than actual counts

70

Without alignments

$p(f \rightarrow e)$: probability that f is aligned to e *in this pair*

a b c

y z

What is $p(y \rightarrow a)$?

Put another way, of all things that y could align to in this sentence, how likely is it to be a?

72

Without alignments

$p(f \rightarrow e)$: probability that f is aligned to e *in this pair*

a b c

y z

Of all things that *y* could align to, how likely is it to be *a*:

p(y | a)

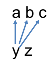
Does that do it?

No! p(y | a) is how likely y is to align to a over the whole data set.

73

Without alignments

$p(f \rightarrow \mathrm{e})$: probability that f is aligned to e *in this pair*



Of all things that *y* could align to, how likely is it to be *a*:

$$\frac{p(y \mid a)}{p(y \mid a) + p(y \mid b) + p(y \mid c)}$$

74

Without the alignments

Input: corpus of English/Foreign sentence pairs (no alignment)

```
for (E, F) in corpus:
    for e in E:
        for f in F:
            p(f → e) = p(f|e)/∑_{e in E} p(f|e)
            count(e,f) += p(f → e)
            count(e) += p(f → e)

for all (e,f) in count:
    p(f|e) = count(e,f) / count(e)
```

75

EM: without the alignments

Input: corpus of English/Foreign sentence pairs (no alignment)

```
for some number of iterations:
    for (E, F) in corpus:
        for e in E:
            for f in F:
                p(f → e) = p(f|e)/∑_{e in E} p(f|e)
                count(e,f) += p(f → e)
                count(e) += p(f → e)

    for all (e,f) in count:
        p(f|e) = count(e,f) / count(e)
```

76

EM: without the alignments

Input: corpus of English/Foreign sentence pairs (no alignment)

```
for some number of iterations:
    for (E, F) in corpus:
        for e in E:
            for f in F:
                p(f → e) = p(f|e)/∑_{e in E} p(f|e)
                count(e,f) += p(f → e)
                count(e) += p(f → e)

    for all (e,f) in count:
        p(f|e) = count(e,f) / count(e)
```

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EM: without the alignments

Input: corpus of English/Foreign sentence pairs (no alignment)

for some number of iterations:
    for (E, F) in corpus:
        for e in E:
            for f in F:
                $p(f \rightarrow e) = p(f|e) / \sum_{e \text{ in } E} p(f|e)$
                count(e,f) += $p(f \rightarrow e)$
                count(e) += $p(f \rightarrow e)$

    for all (e,f) in count:
        p(f|e) = count(e,f) / count(e)

Where are the E and M steps?

78

EM: without the alignments

Input: corpus of English/Foreign sentence pairs (no alignment)

for some number of iterations:
    for (E, F) in corpus:
        for e in E:
            for f in F:
                $p(f \rightarrow e) = p(f|e) / \sum_{e \text{ in } E} p(f|e)$
                count(e,f) += $p(f \rightarrow e)$
                count(e) += $p(f \rightarrow e)$

    for all (e,f) in count:
        p(f|e) = count(e,f) / count(e)

Calculate how probable the alignments are under the current model (i.e. p(f|e))

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EM: without the alignments

Input: corpus of English/Foreign sentence pairs (no alignment)

for some number of iterations:
    for (E, F) in corpus:
        for e in E:
            for f in F:
                $p(f \rightarrow e) = p(f|e) / \sum_{e \text{ in } E} p(f|e)$
                count(e,f) += $p(f \rightarrow e)$
                count(e) += $p(f \rightarrow e)$

    for all (e,f) in count:
        p(f|e) = count(e,f) / count(e)

Recalculate p(f|e) using counts from **all** alignments, **weighted** by how probable they are

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NULL

Sometimes foreign words don't have a direct correspondence to an English word

Adding a NULL word allows for p(f | NULL), i.e. words that appear, but are not associated explicitly with an English word

Implementation: add "NULL" (**or some unique string representing NULL**) to each of the English sentences, often at the beginning of the sentence

p(casa | NULL)	1/3
p(verde | NULL)	1/3
p(la | NULL)	1/3

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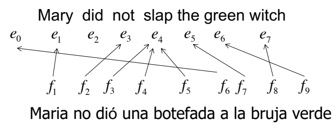
Benefits of word-level model

Rarely used in practice for modern MT system



Two key side effects of training a word-level model:

- Word-level alignment
- p(f | e): translation dictionary

How do I get this?

82

Word alignment

100 iterations

p(casa | green)	0.005
p(verde | green)	0.995
p(la | green)	0

p(casa | house)	~1.0
p(verde | house)	~0.0
p(la | house)	~0.0

p(casa | the)	0.005
p(verde | the)	0
p(la | the)	0.995

green house

casa verde

How should these be aligned?

the house

la casa

83

Word alignment

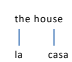
100 iterations

p(casa | green)	0.005
p(verde | green)	0.995
p(la | green)	0

p(casa | house)	~1.0
p(verde | house)	~0.0
p(la | house)	~0.0

p(casa | the)	0.005
p(verde | the)	0
p(la | the)	0.995

Why?



84

Word-level alignment

$$alignment(E,F) = \arg_A \max p(A, F \mid E)$$

Which for IBM model 1 is:

$$alignment(E,F) = \arg_A \max \prod_{i=1}^{|F|} p(f_i \mid e_{a_i})$$

Given a model (i.e. trained p(f|e)), how do we find this?

Align each foreign word (f in F) to the English word (e in E) with highest p(f|e)

$$a_i = \arg_{j:1-|E|} \max p(f_i \mid e_j)$$

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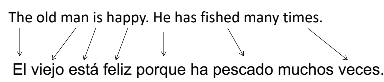
Word-alignment Evaluation



How good of an alignment is this?
How can we quantify this?

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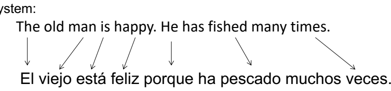
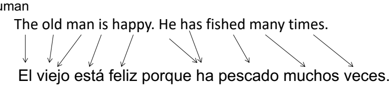
Word-alignment Evaluation

System:



Human

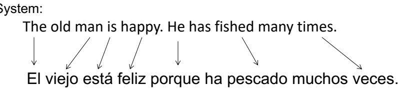


How can we quantify this?

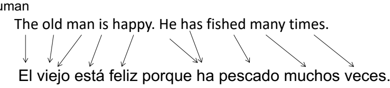
87

Word-alignment Evaluation

System:



Human



Precision and recall!

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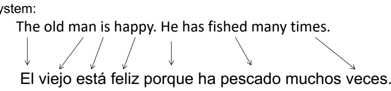
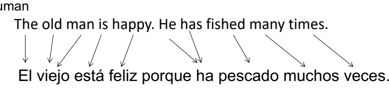
Word-alignment Evaluation

System:



Human



Precision: $\frac{6}{7}$ Recall: $\frac{6}{10}$

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Appendix A

Input: corpus of English/Foreign sentence pairs (no alignment)

```
for some number of iterations:
  for (E, F) in corpus:
    for e in E:
      for f in F:
```
$p(f \rightarrow \mathrm{e}) = \mathrm{p(f|e)}/\sum_{e\ in\ E} p(f|e)$

count(e,f) += $p(f \rightarrow \mathrm{e})$

count(e) += $p(f \rightarrow \mathrm{e})$

```
  for all (e,f) in count:
    p(f|e) = count(e,f) / count(e)
```

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Appendix A

```
for (E, F) in corpus:
  for e in E:
    for f in F:
```
$p(f \rightarrow \mathrm{e}) = \frac{p(f|e)}{\sum_{e\,in\,E} p(f|e)}$

count(e,f) += $p(f \rightarrow \mathrm{e})$

count(e) += $p(f \rightarrow \mathrm{e})$

Pair 1: E: green house
F: casa verde

Pair 2: E: the house
F: la casa

Step 1: calculate p(f -> e) for all pairs of words in the two sentences (assume p(f|e) is a constant for all f,e)

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Appendix A

```
for (E, F) in corpus:
  for e in E:
    for f in F:
```
$p(f \rightarrow \mathrm{e}) = \frac{p(f|e)}{\sum_{e\,in\,E} p(f|e)}$

count(e,f) += $p(f \rightarrow \mathrm{e})$

count(e) += $p(f \rightarrow \mathrm{e})$

Pair 1: E: green house
F: casa verde

Pair 2: E: the house
F: la casa

Step 2: aggregate the counts

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Appendix A

Pair 1: E: green house
F: casa verde

Pair 2: E: the house
F: la casa

```
for all (e,f) in count:
  p(f|e) = count(e,f) / count(e)
```

Step 3: recalculate p(e|f)

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Appendix A

Input: corpus of English/Foreign sentence pairs (no alignment)

for some number of iterations:
  for (E, F) in corpus:
    for e in E:
      for f in F:
        $p(f \rightarrow e) = p(f|e) / \sum_{e\ in\ E} p(f|e)$
        count(e,f) += $p(f \rightarrow e)$
        count(e) += $p(f \rightarrow e)$

  for all (e,f) in count:
    p(f|e) = count(e,f) / count(e)

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Worksheet

Pair 1:
p(casa → green) =
p(casa → house) =
p(verde → green) =
p(verde → house =

Pair 2:
p(la → the) =
p(la → house) =
p(casa → the) =
p(casa → house =

count(green, casa) =
count(green, verde) =

count(house, casa) =
count(house, verde) =
count(house, la) =

count(the, casa) =
count(the, la) =

count(green) =
count(house) =
count(the) =

p(casa | green) =
p(verde | green) =

p(casa | house) =
p(verde | house) =
p(la | house) =

p(casa | the) =
p(la | the) =

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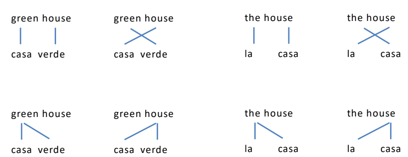

p(casa | green)	1/2
p(verde | green)	1/2
p(la | green)	0

p(casa | house)	1/2
p(verde | house)	1/4
p(la | house)	1/4

p(casa | the)	1/2
p(verde | the)	0
p(la | the)	1/2

c(casa,green) = 1/4+1/4 = 1/2
c(verde,green) = 1/4+1/4 = 1/2
c(la, green) = 0

c(casa,house) = 1/4+1/4+ 1/4+1/4 = 1
c(verde,house) = 1/4+1/4 = 1/2
c(la,house) = 1/4+1/4 = 1/2

c(casa,the) = 1/4+1/4 = 1/2
c(verde,the) = 0
c(la,the) = 1/4+1/4 = 1/2

Then, calculate the probabilities by normalizing the counts

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