

More Word Alignment

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CS159 – Fall 2020

Some slides adapted from

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Admin

Assignment 5a solutions posted

Assignment 5b due Monday

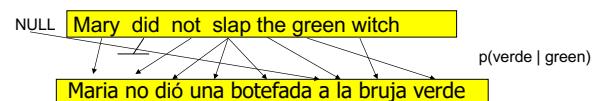
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Language translation



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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!

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

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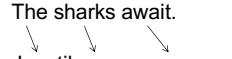
Thought experiment

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.

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

$$p(\text{el} | \text{the}) = 0.5$$

Any problems concerns?

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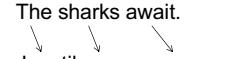
Thought experiment

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


El viejo está feliz porque ha pescado muchos veces.

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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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Training without alignments

a b


How should these be aligned?

c b


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

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Training without alignments

a b

x y

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

What are the possible alignments?

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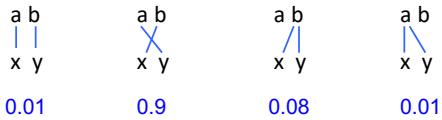
Training without alignments



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

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Training without alignments



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



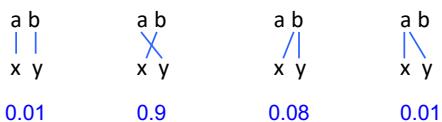
IBM model 1: Each foreign word is aligned to 1 English word

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

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



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



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

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One the other hand

a b
x y

a b
x y

a b
x y

a b
x y

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



If you had $p(f|e)$ could you calculate the probability of the alignments?
 $p(f_i | e_{a_i})$

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One the other hand

a b
x y

a b
x y

a b
x y

a b
x y

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

$$p(\text{alignment1}|F, E) = p(A_1|F, E)$$

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

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

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One the other hand

a b
x y

a b
x y

a b
x y

a b
x y

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

$$p(\text{alignment1}|F, E) = p(A_1|F, E)$$

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

$$p(A, F | E) \quad ? \quad p(A|F, E)$$

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 $p(A_1, F | E)$ 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

a b
| |
x y

a b
X |
x y

a b
/ |
x y

a b
/ \
x y

$$p(x|a)*p(y|b) \quad p(x|b)*p(y|a) \quad p(x|b)*p(y|b) \quad p(x|a)*p(y|a)$$

$$p(F, a_1|E) \quad p(F, a_2|E) \quad p(F, a_3|E) \quad p(F, a_4|E)$$

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

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One the other hand

Alignment 1 Alignment 2 Alignment 3 Alignment 4

a b
| |
x y

a b
X |
x y

a b
/ |
x y

a b
/ \
x y

$$p(x|a)*p(y|b) \quad p(x|b)*p(y|a) \quad p(x|b)*p(y|b) \quad p(x|a)*p(y|a)$$

$$p(F, a_1|E) \quad p(F, a_2|E) \quad p(F, a_3|E) \quad p(F, a_4|E)$$

Normalize

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

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

(Note: theoretical algorithm)

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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

the house

casa verde

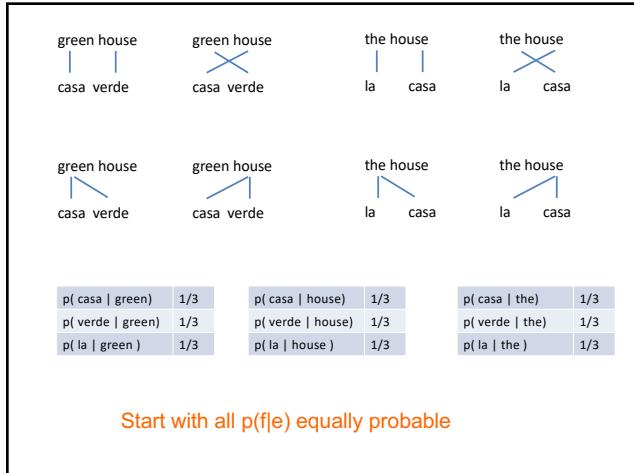
la casa

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

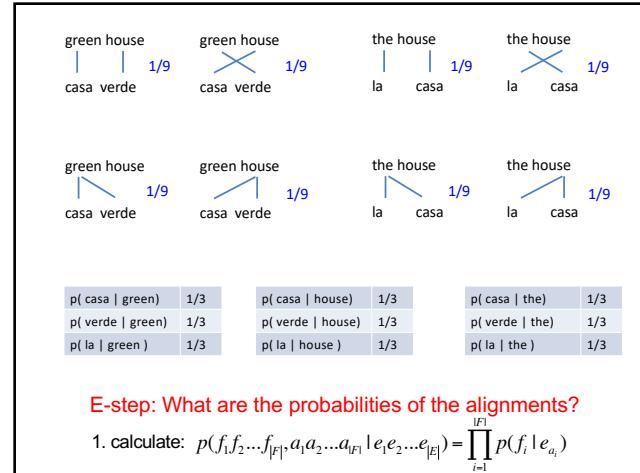
$p(\text{casa} \text{green})$	$p(\text{casa} \text{house})$	$p(\text{casa} \text{the})$
$p(\text{verde} \text{green})$	$p(\text{verde} \text{house})$	$p(\text{verde} \text{the})$
$p(\text{la} \text{green})$	$p(\text{la} \text{house})$	$p(\text{la} \text{the})$

Technically, all combinations of foreign and English words

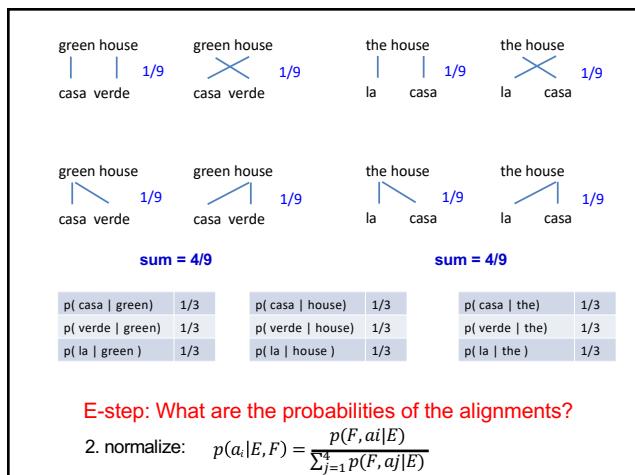
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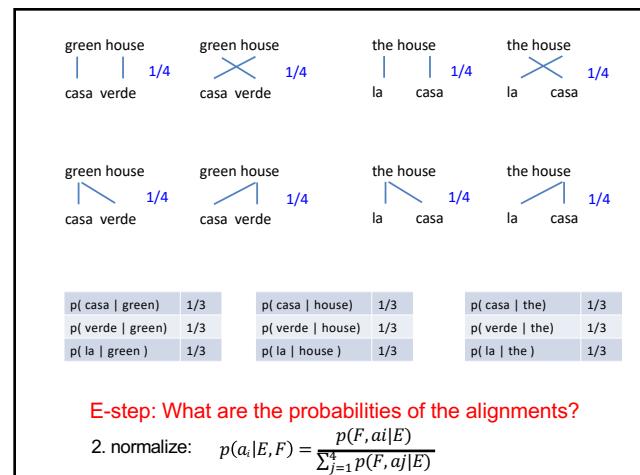
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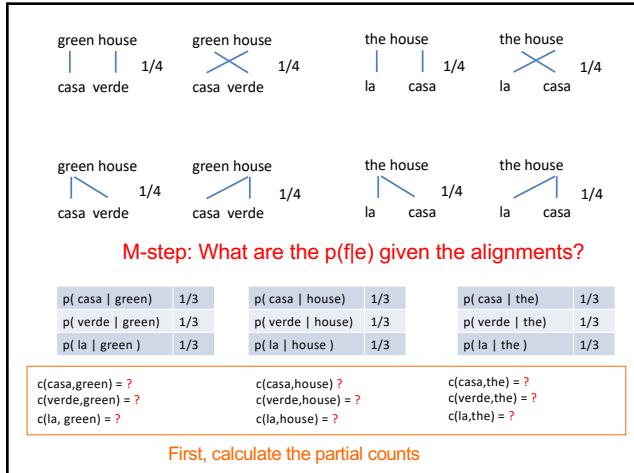
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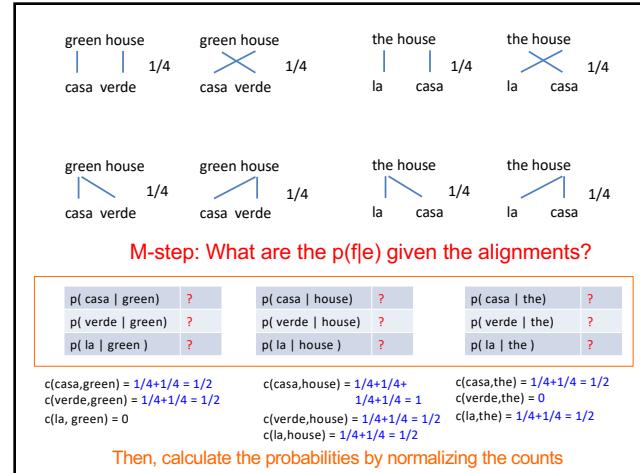
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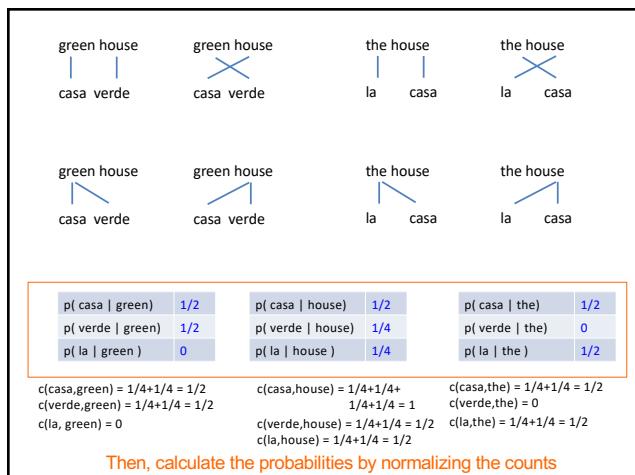
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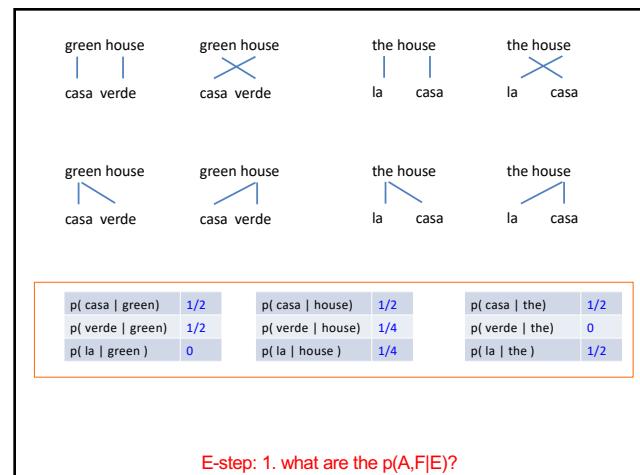
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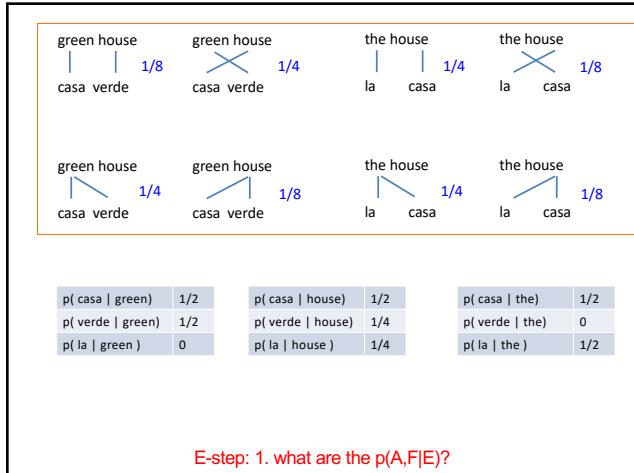
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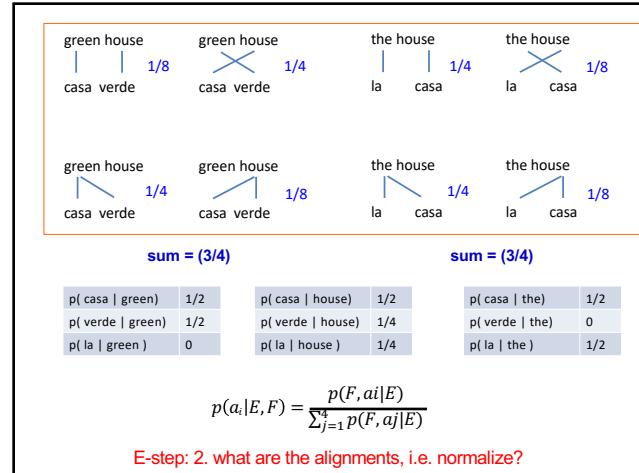
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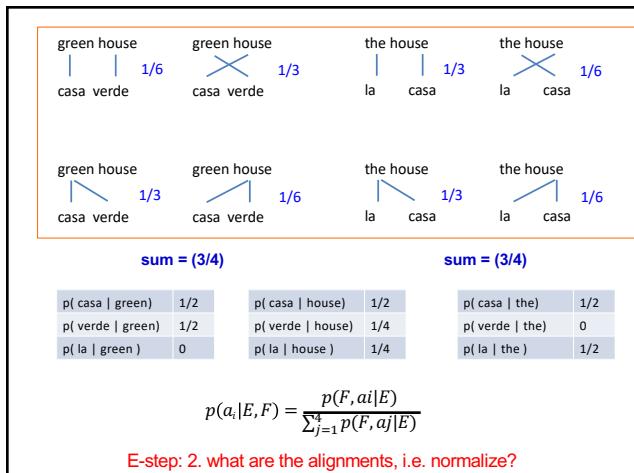
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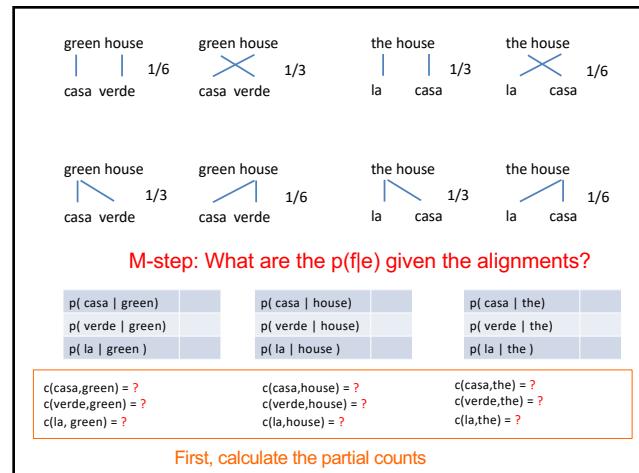
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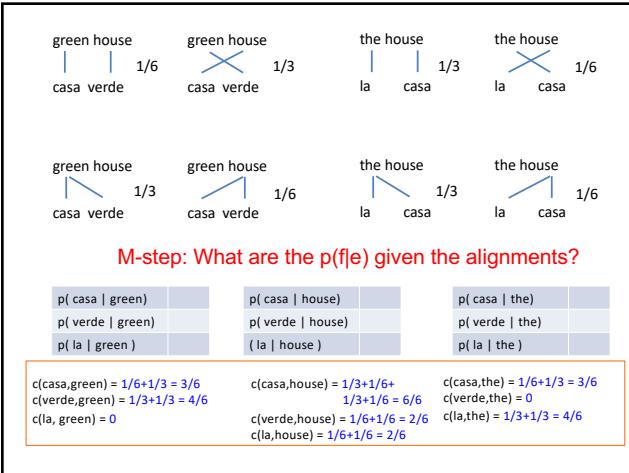
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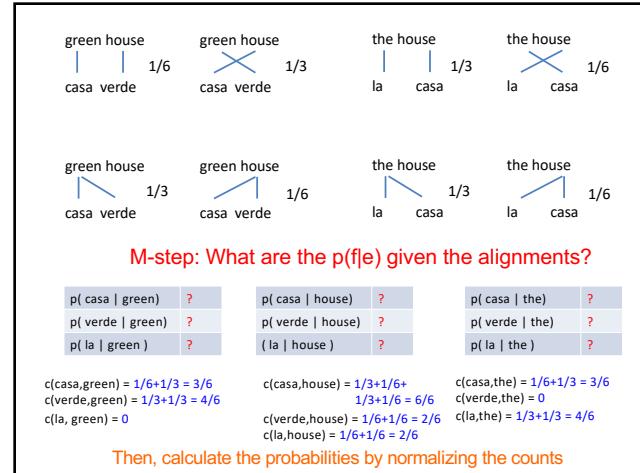
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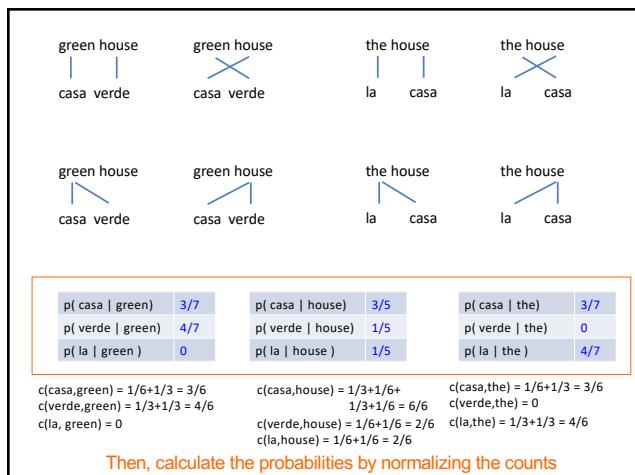
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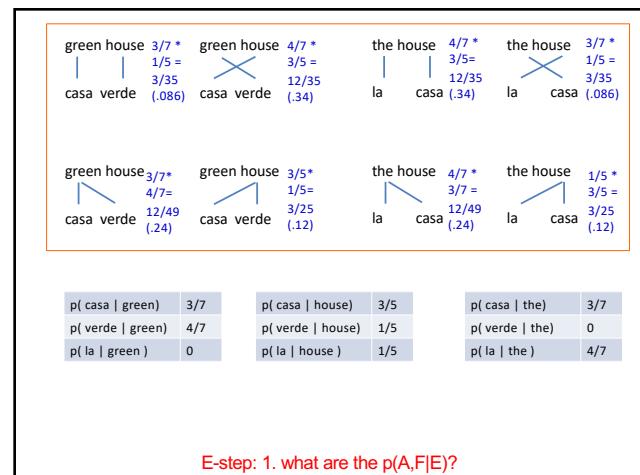
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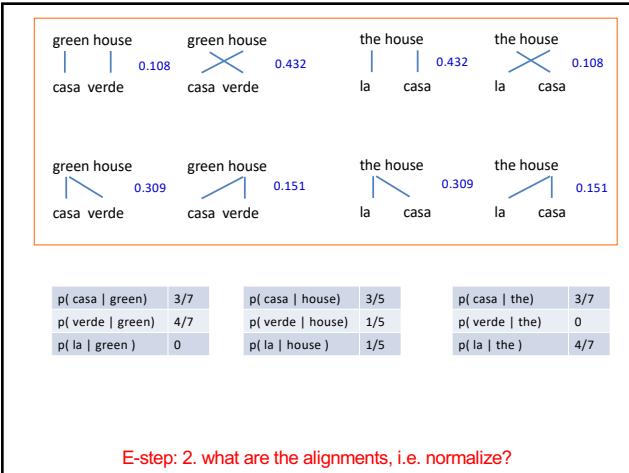
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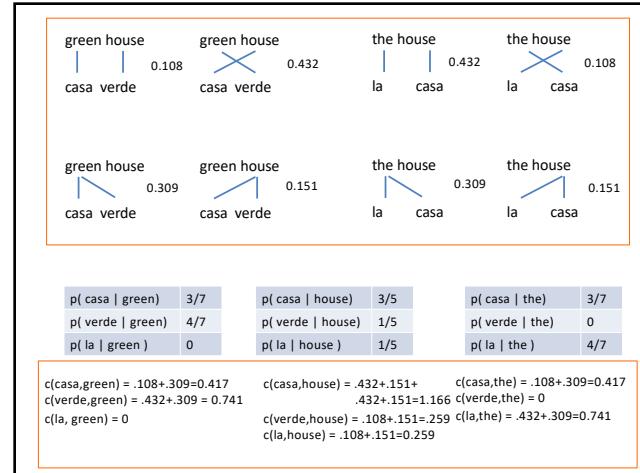
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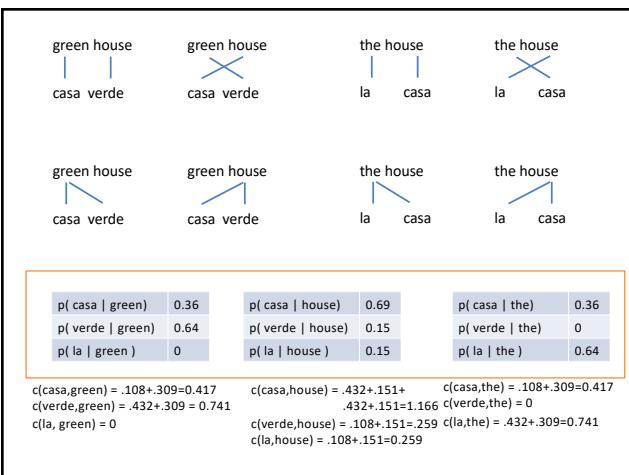
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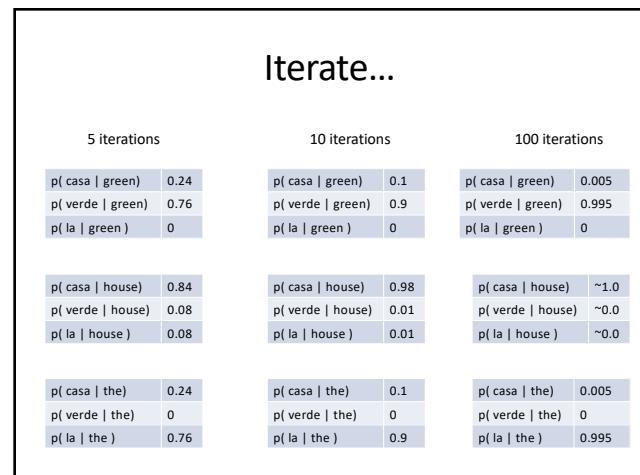
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EM alignment

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?

EM alignment

E-step

-

M-step

-

Why does it work?

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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

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?

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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?

$$p(\text{head}) = 0.60$$

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

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MLE example

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

MLE for heads: $p(\text{head}) = 0.60$

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

$$\text{likelihood}(\text{data}) = \prod_i p(x_i)$$

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

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MLE example

Can we do any better?

$$\text{likelihood}(\text{data}) = \prod_i p(x_i)$$

$$p(\text{heads}) = 0.5$$

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

$$p(\text{heads}) = 0.7$$

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

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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:

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

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

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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

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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

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Implementation details

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

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.

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

$$\begin{aligned} p(\text{el} | \text{the}) &= 0.5 \\ p(\text{los} | \text{the}) &= 0.5 \end{aligned}$$

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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)
```

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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)
```

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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
```

Are these equivalent?

```
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)
```

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