CS447: Natural Language Processing

http://courses.engr.illinois.edu/cs447

Lecture 14: Statistical Machine Translation

Julia Hockenmaier

juliahmr@illinois.edu

3324 Siebel Center

Lecture 14:
Machine Translation II

Part 1: Word Alignment in the IBM models

Statistical Machine Translation

Given a Chinese input sentence (**source**)…

主席：各位議員，早晨。

…find the best English translation (**target**)

President: Good morning, Honourable Members.

We can formalize this as $T^* = \text{argmax}_T P(T \mid S)$

Using **Bayes Rule** simplifies the modeling task, so this was the first approach for statistical MT (the so-called "**noisy-channel model**"):

$$T^* = \text{argmax}_T P(T \mid S) = \text{argmax}_T P(S \mid T) P(T)$$

where $P(S \mid T)$: translation model

$P(T)$: language model

The noisy channel model

This is really just an application of **Bayes' rule**:

$$T^* = \text{argmax}_T \; P(T \mid S)$$

$$= \text{argmax}_T \; \underbrace{P(S \mid T)}_{\text{Translation Model}} \; \underbrace{P(T)}_{\text{Language Model}}$$

The **translation model** $P(S \mid T)$ is intended to capture the **faithfulness** of the translation. [this is the noisy channel]

Since we only need $P(S \mid T)$ to score S, and don't need it to generate a grammatical S, it can be a relatively simple model.

$P(S \mid T)$ needs to be trained on a **parallel corpus**

The **language model** $P(T)$ is intended to capture the **fluency** of the translation.

$P(T)$ can be trained on a (very large) **monolingual corpus**

IBM models

First statistical MT models, based on noisy channel:

Translate from (French/foreign) source $\mathbf{f}$ to (English) target $\mathbf{e}$
via a **translation model** $P(\mathbf{f} \mid \mathbf{e})$ and a **language model** $P(\mathbf{e})$
The translation model goes **from target $\mathbf{e}$ to source $\mathbf{f}$**
via **word alignments $\mathbf{a}$**: $P(\mathbf{f} \mid \mathbf{e}) = \sum_{\mathbf{a}} P(\mathbf{f}, \mathbf{a} \mid \mathbf{e})$

Original purpose: Word-based translation models
Later: Were used to obtain word alignments,
which are then used to obtain phrase alignments
for phrase-based translation models

Sequence of 5 translation models

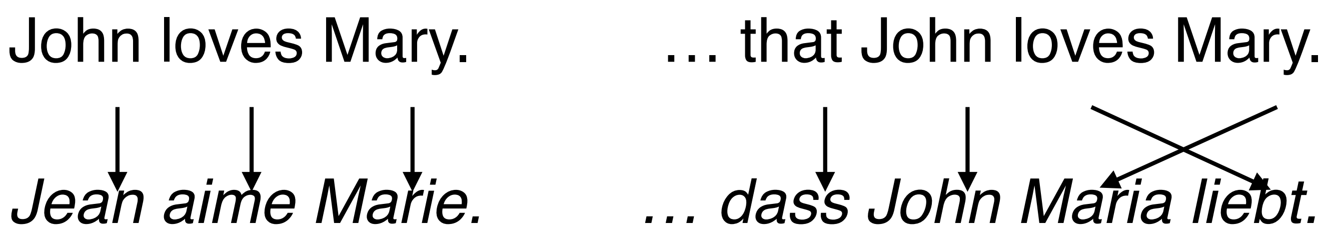
Model 1 is too simple to be used by itself,
but can be trained very easily on parallel data.

IBM translation models: assumptions

The model "generates" the 'foreign' source sentence $\mathbf{f}$ conditioned on the 'English' target sentence $\mathbf{e}$ by the following stochastic process:

1. Generate the **length** of the source $\mathbf{f}$ with probability $p = ...$
2. Generate the **alignment** of the source $\mathbf{f}$ to the target $\mathbf{e}$ with probability $p = ...$
3. Generate the **words** of the source $\mathbf{f}$ with probability $p = ...$

Word alignment



	Jean	aime	Marie
John	■		
loves		■	
Mary			■

	dass	John	Maria	liebt
that	■			
John		■		
loves				■
Mary			■	

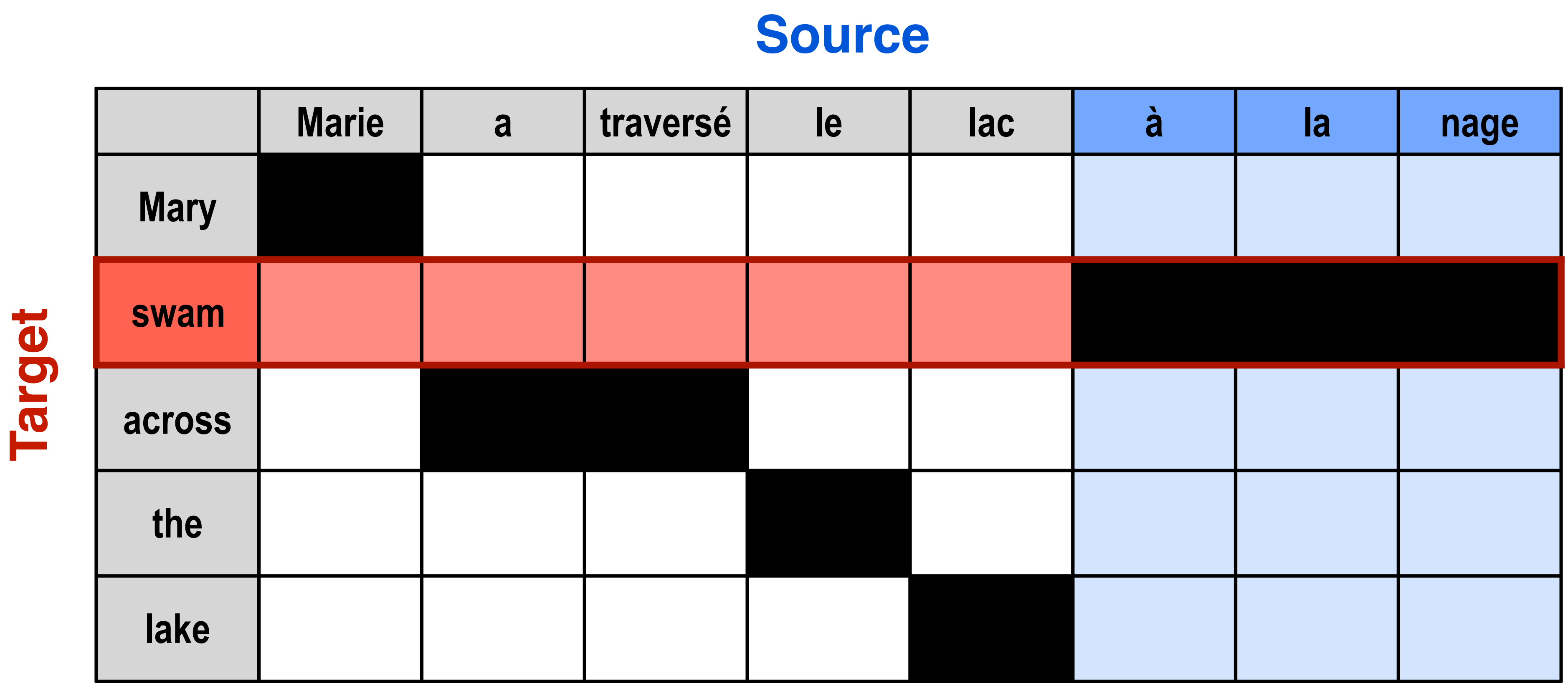
Word alignment

	Maria	no	dió	una	bofetada	a	la	bruja	verde
Mary	■								
did		■							
not		■							
slap			■	■	■				
the						■	■		
green									■
witch								■	

Word alignment

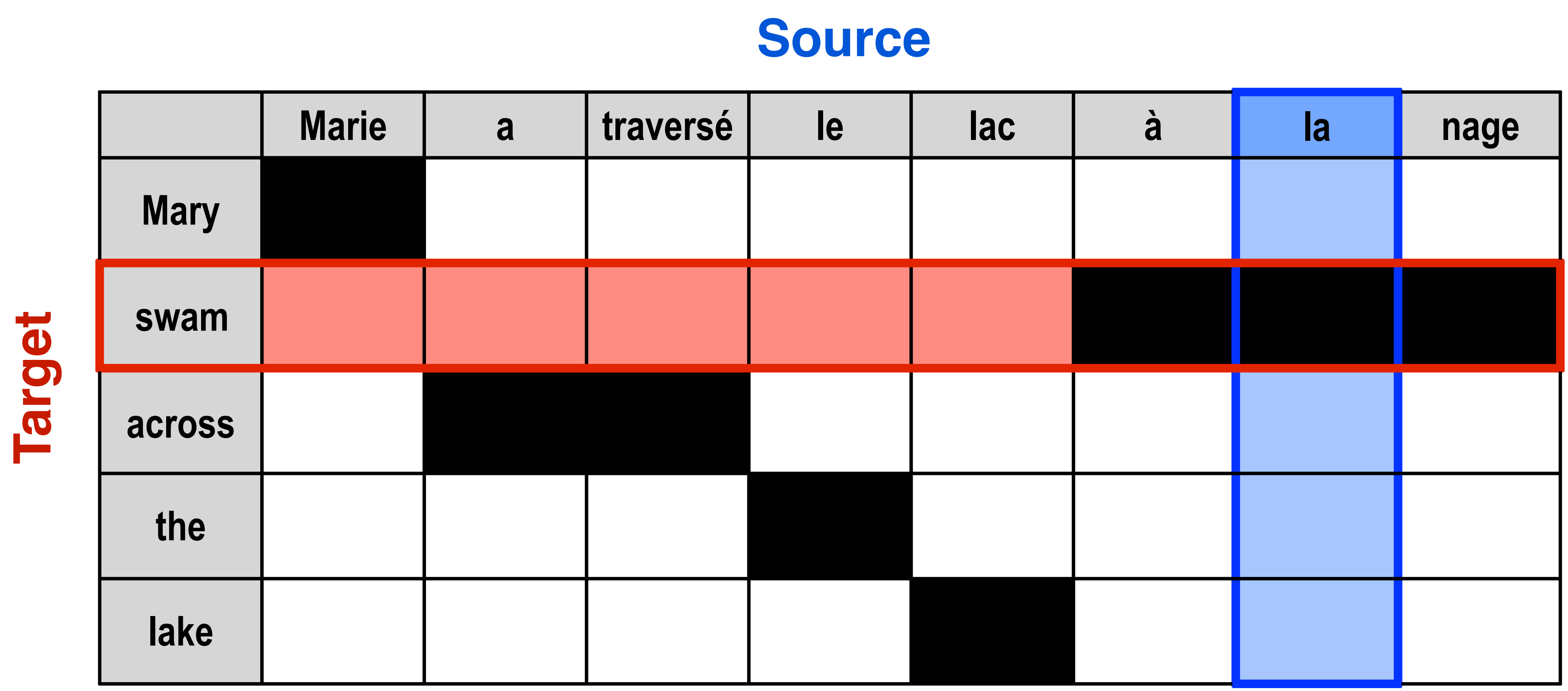
	Marie	a	traversé	le	lac	à	la	nage
Mary	■							
swam						■	■	■
across		■	■					
the				■				
lake					■			

Word alignment



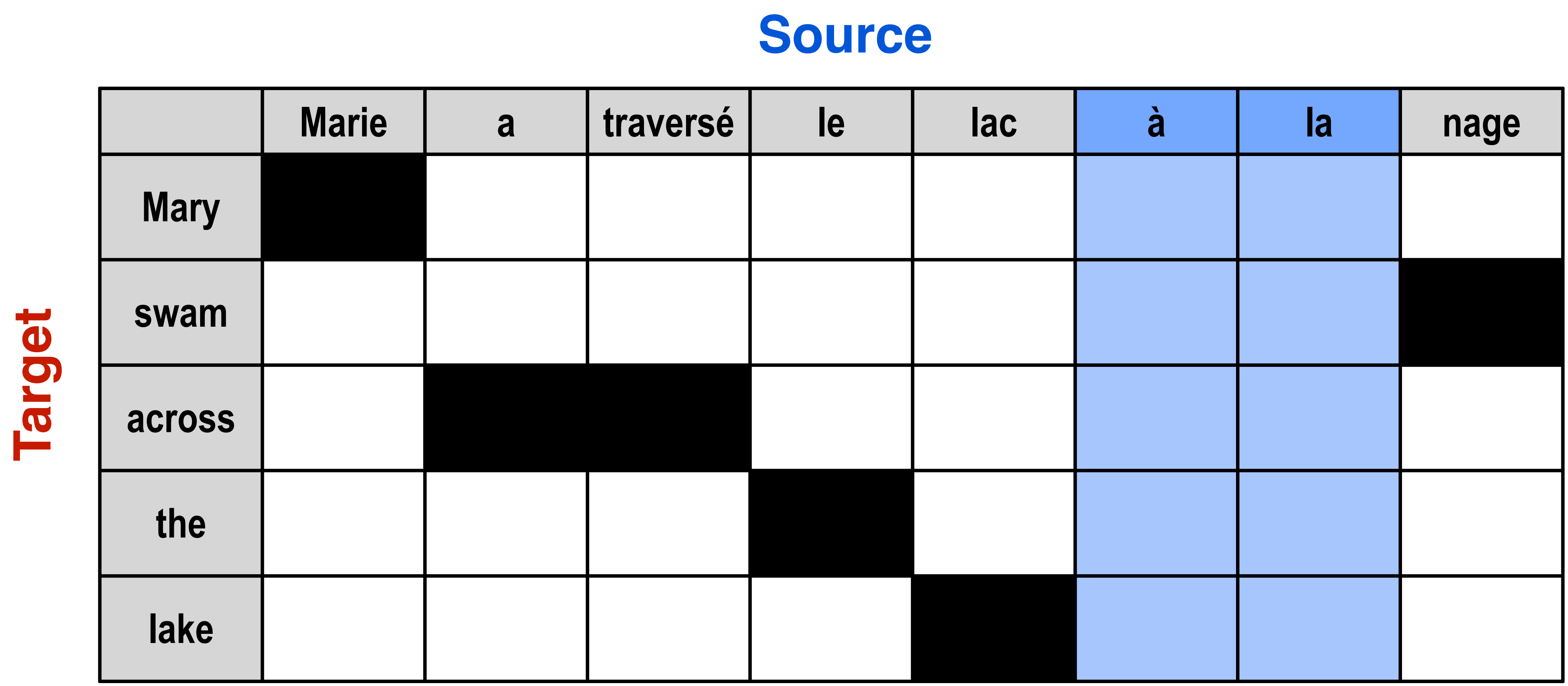
One target word can be aligned to **many source words**.

Word alignment



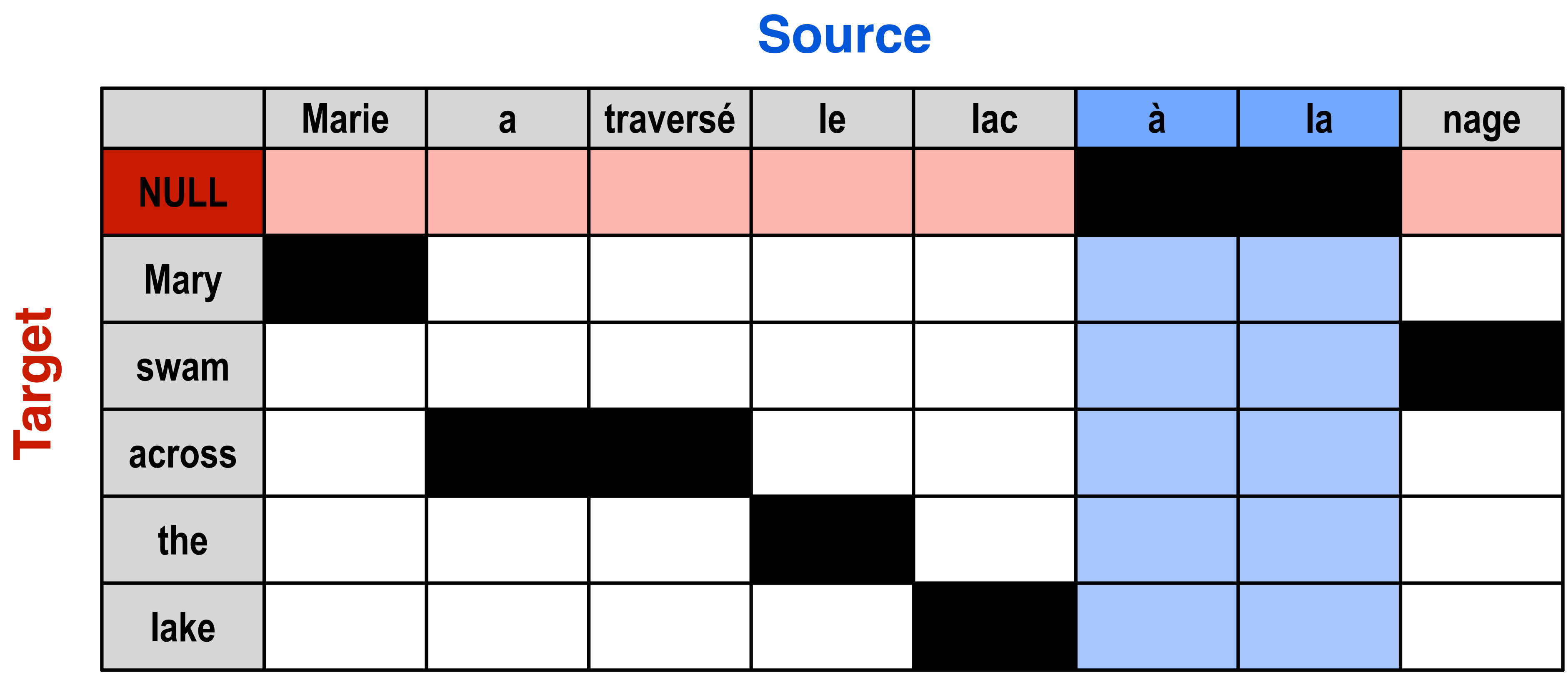
One target word can be aligned to **many source words**.
But **each source word** can only be aligned to **one target word.**
This allows us to model ***P*(source | target)**

Word alignment



Some source words may **not align** to ***any* target words**.

Word alignment



Some source words may **not align** to ***any* target words**.
To handle this we assume a NULL word in the target sentence.

Representing word alignments

		1	2	3	4	5	6	7	8
		Marie	a	traversé	le	lac	à	la	nage
0	NULL						■	■	
1	Mary	■							
2	swam								■
3	across		■	■					
4	the				■				
5	lake					■			

Position	1	2	3	4	5	6	7	8
Foreign	Marie	a	traversé	le	lac	à	la	nage
Alignment	1	3	3	4	5	0	0	2

Every source word **f[i]** is aligned to **one** target word **e[j]** (incl. NULL).
We represent alignments as a vector **a** (of the same length as the source) with **a[i] = j**

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Part 2: The IBM alignment models

The IBM models

Use the noisy channel (Bayes rule) to get the best (most likely) target translation $\mathbf{e}$ for source sentence $\mathbf{f}$:

$$\arg\max_{\mathbf{e}} P(\mathbf{e}|\mathbf{f}) = \arg\max_{\mathbf{e}} P(\mathbf{f}|\mathbf{e})P(\mathbf{e})$$

noisy channel

The translation model $P(\mathbf{f} \mid \mathbf{e})$ requires **alignments** $\mathbf{a}$

$$P(\mathbf{f}|\mathbf{e}) = \sum_{\mathbf{a}\in\mathcal{A}(\mathbf{e},\mathbf{f})} P(\mathbf{f},\mathbf{a}|\mathbf{e})$$

marginalize (=sum) over all alignments a

Generate $\mathbf{f}$ and the alignment $\mathbf{a}$ with $P(\mathbf{f}, \mathbf{a} \mid \mathbf{e})$:

$$P(\mathbf{f},\mathbf{a}|\mathbf{e}) = \underbrace{P(m|\mathbf{e})}_{\text{Length: }|\mathbf{f}|=m} \prod_{j=1}^{m} \underbrace{P(a_j|a_{1..j-1}, f_{1..j-1}, m, \mathbf{e})}_{\text{Word alignment } a_j} \underbrace{P(f_j|a_{1..j} f_{1..j-1}, \mathbf{e}, m)}_{\text{Translation } f_j}$$

m = #words in fj

probability of alignment aj

probability of word fj

IBM model 1: Generative process

For each target sentence $\mathbf{e} = e_1..e_n$ of length n:

0	1	2	3	4	5
NULL	**Mary**	**swam**	**across**	**the**	**lake**

1. **Choose a length** m for the source sentence (e.g $m = 8$)

Position	1	2	3	4	5	6	7	8

2. **Choose an alignment** $\mathbf{a} = a_1...a_m$ for the source sentence

Each a_j corresponds to a word e_i in $\mathbf{e}$: $0 \leq a_j \leq n$

Position	1	2	3	4	5	6	7	8
Alignment	1	3	3	4	5	0	0	2

3. **Translate each target word** e_{a_j} into the source language

Position	1	2	3	4	5	6	7	8
Alignment	1	3	3	4	5	0	0	2
Translation	**Marie**	**a**	**traversé**	**le**	**lac**	**à**	**la**	**nage**

Model parameters

Length probability $P(m \mid n)$:

What's the probability of generating a source sentence of length m given a target sentence of length n?
Count in training data, or use a constant

Alignment probability: $P(\mathbf{a} \mid m, n)$:

Model 1 assumes all alignments have the same probability:
For each position $a_1 ... a_m$, pick one of the $n+1$ target positions uniformly at random

Translation probability: $P(f_j = lac \mid a_j = i, e_i = lake)$:

In Model 1, these are the only parameters we have to learn.

IBM model 1: details

The **length probability** is constant: $P(m \mid \mathrm{e}) = \varepsilon$

The **alignment probability** is uniform
(n = length of target string): $P(a_i \mid \mathrm{e}) = 1/(n+1)$

The **translation probability** depends only on e_{ai}
(the corresponding target word): $P(f_i \mid \mathrm{e}_{ai})$

$$P(\mathbf{f}, \mathbf{a} | \mathbf{e}) = \underbrace{P(m|\mathbf{e})}_{\text{Length: } |\mathbf{f}|=m} \prod_{j=1}^{m} \underbrace{P(a_j | a_{1..j-1}, f_{1..j-1}, m, \mathbf{e})}_{\text{Word alignment } a_j} \underbrace{P(f_j | a_{1..j} f_{1..j-1}, \mathbf{e}, m)}_{\text{Translation } f_j}$$

$$= \epsilon \prod_{j=1}^{m} \frac{1}{n+1} P(f_j | e_{a_j})$$

$$\frac{\epsilon}{(n+1)^m} \prod_{j=1}^{m} P(f_j | e_{a_j})$$

All alignments have the same probability

Translation depends only on the aligned English word

Finding the best alignment

How do we find the **best alignment** between $\mathbf{e}$ and $\mathbf{f}$?

$$\begin{aligned}
\hat{\mathbf{a}} &= \arg\max_{\mathbf{a}} P(\mathbf{f}, \mathbf{a} | \mathbf{e}) \\
&= \arg\max_{\mathbf{a}} \frac{\epsilon}{(n+1)^m} \prod_{j=1}^{m} P(f_j | e_{a_j}) \\
&= \arg\max_{\mathbf{a}} \prod_{j=1}^{m} P(f_j | e_{a_j})
\end{aligned}$$

$$\hat{a}_j = \arg\max_{a_j} P(f_j | e_{a_j})$$

Learning translation probabilities

The only parameters that need to be learned are the **translation probabilities** $P(\mathrm{f} \mid \mathrm{e})$

$$P(\mathrm{f}_\mathrm{j} = lac \mid \mathrm{e}_\mathrm{i} = lake)$$

If the training corpus had word alignments, we could simply count how often 'lake' is aligned to 'lac':

$$P(lac \mid lake) = \mathrm{count}(lac, lake) \,/\, \textstyle\sum_w \mathrm{count}(w, lake)$$

But we don't have gold word alignments.

So, instead of relative frequencies, we have to use *expected* relative frequencies:

$$P(\, lac \mid lake) = \langle \mathrm{count}(lac, lake) \rangle \,/\, \langle \textstyle\sum_w \mathrm{count}(w, lake) \rangle$$

Training Model 1 with EM

The only parameters that need to be learned are the **translation probabilities** $P(\mathrm{f} \mid \mathrm{e})$

We use the **EM algorithm** to estimate these parameters from a corpus with S sentence pairs $\boldsymbol{s} = \langle \boldsymbol{f}^{(s)}, \boldsymbol{e}^{(s)} \rangle$ with alignments $A(\mathbf{f}^{(s)}, \mathbf{e}^{(s)})$

Initialization: guess $P(\mathrm{f} \mid \mathrm{e})$

Expectation step: compute expected counts

$$\langle c(f, e) \rangle = \sum_{s \in S} \langle c(f, e | \mathbf{e}^{(s)}, \mathbf{f}^{(s)}) \rangle$$

Maximization step: recompute probabilities $P(\mathrm{f} \mid \mathrm{e})$

$$\hat{P}(f|e) = \frac{\langle c(f, e) \rangle}{\sum_{f'} \langle c(f', e) \rangle}$$

Expectation-Maximization (EM)

1. Initialize a first model, $M^{(0)}$

2. Expectation (E) step:
   Go through training data to gather expected counts
   $\langle \text{count}(lac, lake) \rangle$

3. Maximization (M) step:
   Use expected counts to compute a new model $M^{(i+1)}$
   $P^{(i+1)}(\, lac \mid lake) = \langle \text{count}(lac, lake) \rangle / \langle \sum w \text{ count}(w, lake) \rangle$

4. Check for convergence:
   Compute log-likelihood of training data with M_{i+1}
   If the difference between new and old log-likelihood smaller than a threshold, stop. Else go to 2.

The E-step

Compute the expected count $\langle c(f,e|\mathbf{f},\mathbf{e})\rangle$:

$$\langle c(f,e|\mathbf{f},\mathbf{e})\rangle = \sum_{\mathbf{a}\in\mathcal{A}(\mathbf{f},\mathbf{e})} P(\mathbf{a}|\mathbf{f},\mathbf{e}) \cdot \underbrace{c(f,e|\mathbf{a},\mathbf{e},\mathbf{f})}_{\text{How often are } f,e \text{ aligned in } \mathbf{a}?}$$

$$P(\mathbf{a}|\mathbf{f},\mathbf{e}) = \frac{P(\mathbf{a},\mathbf{f}|\mathbf{e})}{P(\mathbf{f}|\mathbf{e})} = \frac{P(\mathbf{a},\mathbf{f}|\mathbf{e})}{\sum_{\mathbf{a}'} P(\mathbf{a}',\mathbf{f}|\mathbf{e})}$$

$$P(\mathbf{a},\mathbf{f}|\mathbf{e}) = \prod_j P(f_j|e_{a_j})$$

$$\langle c(f,e|\mathbf{f},\mathbf{e})\rangle = \sum_{\mathbf{a}\in\mathcal{A}(\mathbf{f},\mathbf{e})} \frac{\prod_j P(f_j|e_{a_j})}{\sum_{a'}\prod_j P(f_j|e_{a'_j})} \cdot c(f,e|\mathbf{a},\mathbf{e},\mathbf{f})$$

We need to know $P(f_j|e_{a_j})$, the probability that word f_j is aligned to word e_{aj} under the alignment a

Other translation models

Model 1 is a very simple (and not very good) translation model.

IBM models 2-5 are more complex. They take into account:

– **“fertility”:** the number of foreign words generated by each target word
– the **word order** and **string position** of the aligned words

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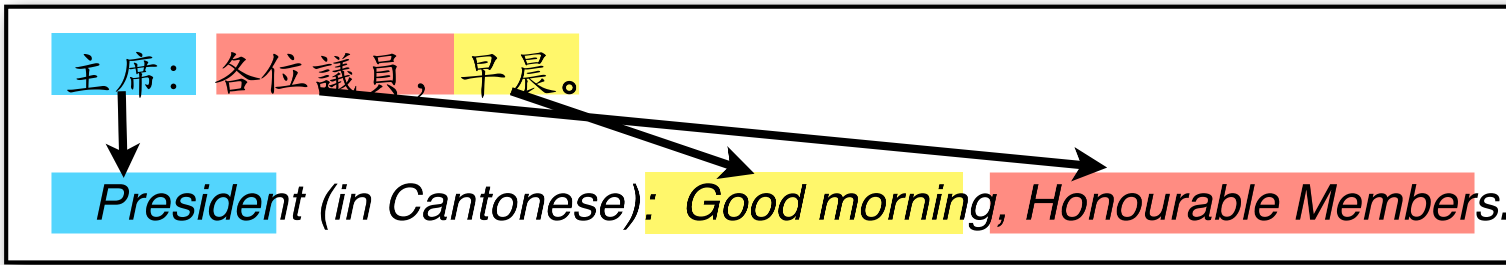
Part 3: Phrase-based translation models

Phrase-based translation models

Assumption: fundamental units of translation are **phrases**:



Phrase-based model of $P(F \mid E)$:

1. Split target sentence deterministically into phrases $ep_1 \ldots ep_n$
2. Translate each target phrase ep_i into source phrase fp_i with translation probability $\varphi(fp_i \mid ep_i)$
3. Reorder foreign phrases with distortion probability $d(a_i - b_{i-1}) = c^{|a_i - b_{i-1} - 1|}$

a_i = start position of source phrase generated by e_i

b_{i-1} = end position of source phrase generated by e_{i-1}

Phrase-based models of $P(f \mid e)$

Split target sentence $e = e_{1..n}$ into phrases $\mathbf{ep}_1..\mathbf{ep}_N$:

[***The green witch***] [***is***] [***at home***] [***this week***]

Translate each target phrase $\mathbf{ep}_i$ into source phrase $\mathbf{fp}_i$ with **translation probability** $P(fp_i \mid ep_i)$:

[***The green witch***] = [***die grüne Hexe***], …

Arrange the set of source phrases $\{fp_i\}$ to get $\mathbf{s}$ with **distortion probability** $P(fp \mid \{fp_i\})$:

[***Diese Woche***] [***ist***] [***die grüne Hexe***] [***zuhause***]

$$P(\mathbf{f} \mid \mathbf{e} = \langle ep_1, ..., ep_l \rangle) = \prod_i P(fp_i \mid ep_i) P(\mathbf{fp} \mid \{fp_i\})$$

Translation probability $P(fp_i \mid ep_i)$

Phrase translation probabilities can be obtained from a **phrase table:**

EP	**FP**	**count**
green witch	grüne Hexe	…
at home	zuhause	10534
at home	daheim	9890
is	ist	598012
this week	diese Woche	….

This requires **phrase alignment**

Word alignment

	Diese	Woche	ist	die	grüne	Hexe	zuhause
The				■			
green					■		
witch						■	
is			■				
at							
home							■
this	■						
week		■					

Phrase alignment

Obtaining phrase alignments

We'll skip over details, but here's the basic idea:

For a given parallel corpus (F—E)

1. Train **two word aligners**, (F→E and E→F)
2. Take the **intersection** of these alignments
   to get a **high-precision** word alignment
3. **Grow** these high-precision alignments
   until all words in both sentences are included
   in the alignment.

   Consider any pair of words in the **union** of the alignments, and incrementally add them to the existing alignments
4. Consider all phrases that are **consistent** with
   this improved word alignment

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Part 4: Decoding (for phrase-based MT)

Phrase-based models of $P(f \mid e)$

Split target sentence $e = e_{1..n}$ into phrases $\mathbf{ep}_1..\mathbf{ep}_N$:

[*The green witch*] [*is*] [*at home*] [*this week*]

Translate each target phrase $\mathbf{ep}_i$ into source phrase $\mathbf{fp}_i$ with **translation probability** $P(fp_i \mid ep_i)$:

[*The green witch*] = [*die grüne Hexe*], ...

Arrange the set of source phrases $\{fp_i\}$ to get $\mathbf{s}$ with **distortion probability** $P(fp \mid \{fp_i\})$:

[*Diese Woche*] [*ist*] [*die grüne Hexe*] [*zuhause*]

$$P(\mathbf{f} \mid \mathbf{e} = \langle ep_1, ..., ep_l \rangle) = \prod_i P(fp_i \mid ep_i) P(\mathbf{fp} \mid \{fp_i\})$$

Translating

How do we translate a foreign sentence (e.g. *“Diese Woche ist die grüne Hexe zuhause”*) into English?

- We need to find $\hat{e} = argmaxe\, P(f \mid e)P(e)$
- There is an exponential number of candidate translations e
- But we can look up phrase translations ep and $P(\, fp \mid ep\,)$ in the phrase table:

<table>
<tr><th>diese</th><th>Woche</th><th>ist</th><th>die</th><th>grüne</th><th>Hexe</th><th>zuhause</th></tr>
<tr><td>this 0.2</td><td>week 0.7</td><td>is 0.8</td><td>the 0.3</td><td>green 0.3</td><td>witch 0.5</td><td>home 1.00</td></tr>
<tr><td>these 0.5</td><td colspan="2"></td><td colspan="2">the green 0.4</td><td>sorceress 0.6</td><td rowspan="3"></td></tr>
<tr><td colspan="2">this week 0.6</td><td colspan="2"></td><td colspan="2">green witch 0.7</td></tr>
<tr><td colspan="3">is this week 0.4</td><td colspan="3">the green witch 0.7</td></tr>
</table>

Generating a (random) translation

1. Pick the first Target phrase $\boldsymbol{ep}_1$ from the candidate list.

$$P := P_{LM}(\langle s\rangle\ \boldsymbol{ep}_1)P_{Trans}(\boldsymbol{fp}_1 \mid \boldsymbol{ep}_1)$$

E = the, F= <….die…>

2. Pick the next target phrase $\boldsymbol{ep}_2$ from the candidate list

$$P := P \times P_{LM}(\boldsymbol{ep}_2 \mid \boldsymbol{ep}_1)P_{Trans}(\boldsymbol{fp}_2 \mid \boldsymbol{ep}_2)$$

E = the green witch, F = <….die grüne Hexe…>

3. Keep going: pick target phrases $\boldsymbol{ep}_i$ until the entire source sentence is translated

$$P := P \times P_{LM}(\boldsymbol{ep}_i \mid \boldsymbol{ep}_{1\ldots i-1})P_{Trans}(\boldsymbol{fp}_i \mid \boldsymbol{ep}_i)$$

E = the green witch is, F = <….ist die grüne Hexe…>

<table>
<tr><th>diese</th><th>Woche</th><th>ist</th><th>die</th><th>grüne</th><th>Hexe</th><th>zuhause</th></tr>
<tr><td>this 0.2</td><td>week 0.7</td><td>(3) is 0.8</td><td>(1) the 0.3</td><td>green 0.3</td><td>witch 0.5</td><td>(5) at home 0.5</td></tr>
<tr><td>these 0.5</td><td colspan="2"></td><td colspan="2">the green 0.4</td><td>sorceress 0.6</td><td></td></tr>
<tr><td colspan="2">(4) this week 0.6</td><td colspan="2"></td><td colspan="2">(2) green witch 0.7</td><td></td></tr>
<tr><td colspan="3">is this week 0.4</td><td colspan="3">the green witch 0.7</td><td></td></tr>
</table>

Finding the best translation

How can we find the *best* translation efficiently?

There is an exponential number of possible translations.

We will use a *heuristic* search algorithm

We cannot guarantee to find the best (= highest-scoring) translation, but we're likely to get close.

We will use a *"stack-based"* decoder

(If you've taken Intro to AI: this is A* ("A-star") search)

We will score partial translations based on how good we expect the corresponding completed translation to be.

Or, rather: we will score partial translations on how **bad** we expect the corresponding complete translation to be.
That is, our scores will be **costs (high=bad, low=good)**

Scoring partial translations

Assign expected costs to *partial* translations (E, F):

$$expected\_cost(E,F) = current\_cost(E,F) + future\_cost(E,F)$$

The current cost is based on the score of the partial translation (E, F)

e.g. $current\_cost(E,F) = \log P(E)P(F \mid E)$

The (estimated) future cost is a **lower bound** on the actual cost of completing the partial translation (E, F):

$$true\_cost(E,F) \quad (= current\_cost(E,F) + actual\_future\_cost(E,F))$$
$$\geq expected\_cost(E,F) \quad (= current\_cost(E,F) + est\_future\_cost(E,F))$$

because $actual\_future\_cost(E,F) \geq est\_future\_cost(E,F)$

(The estimated future cost ignores the distortion cost)

Stack-based decoding

Maintain a **priority queue** (='stack') of **partial translations** (hypotheses) with their **expected costs**.

Each element on the stack is **open** (we haven't yet pursued this hypothesis) or **closed** (we have already pursued this hypothesis)

At each step:

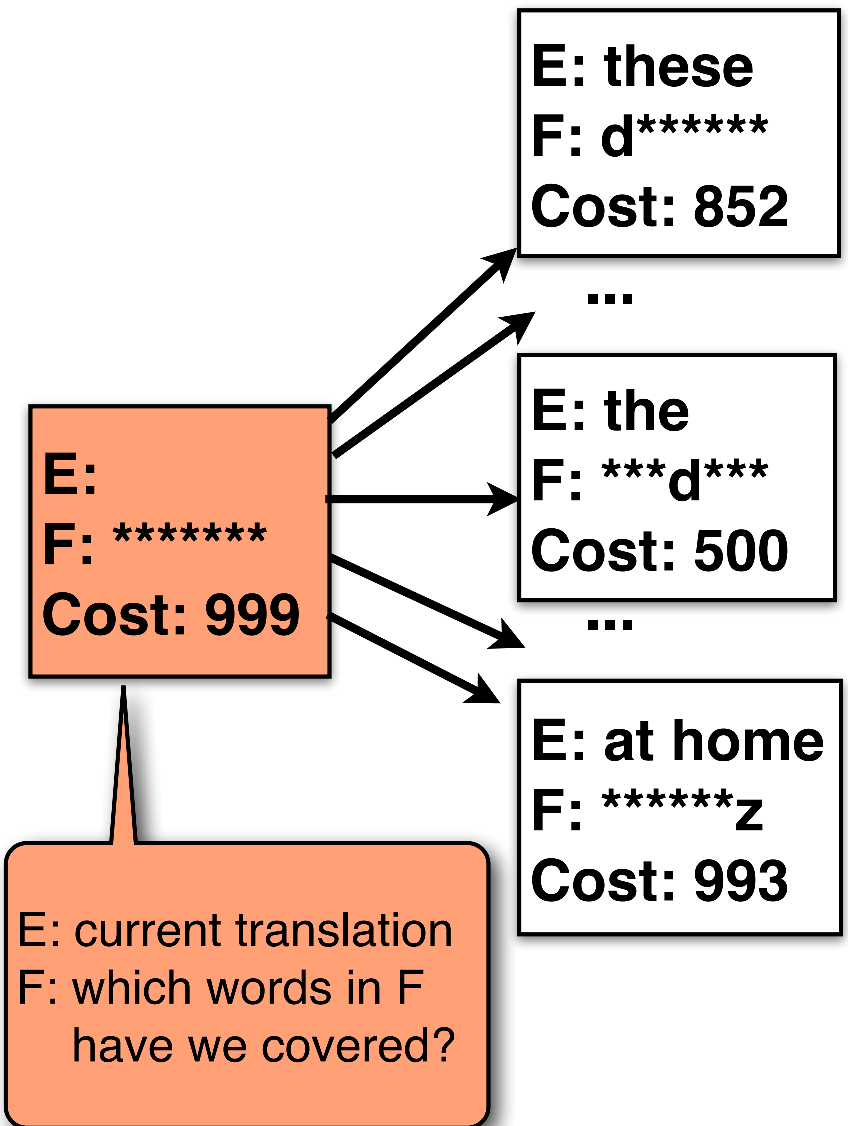
—**Expand** the best open hypothesis (the open translation with the lowest expected cost) in all possible ways.

—These new translations become new **open elements** on the stack.

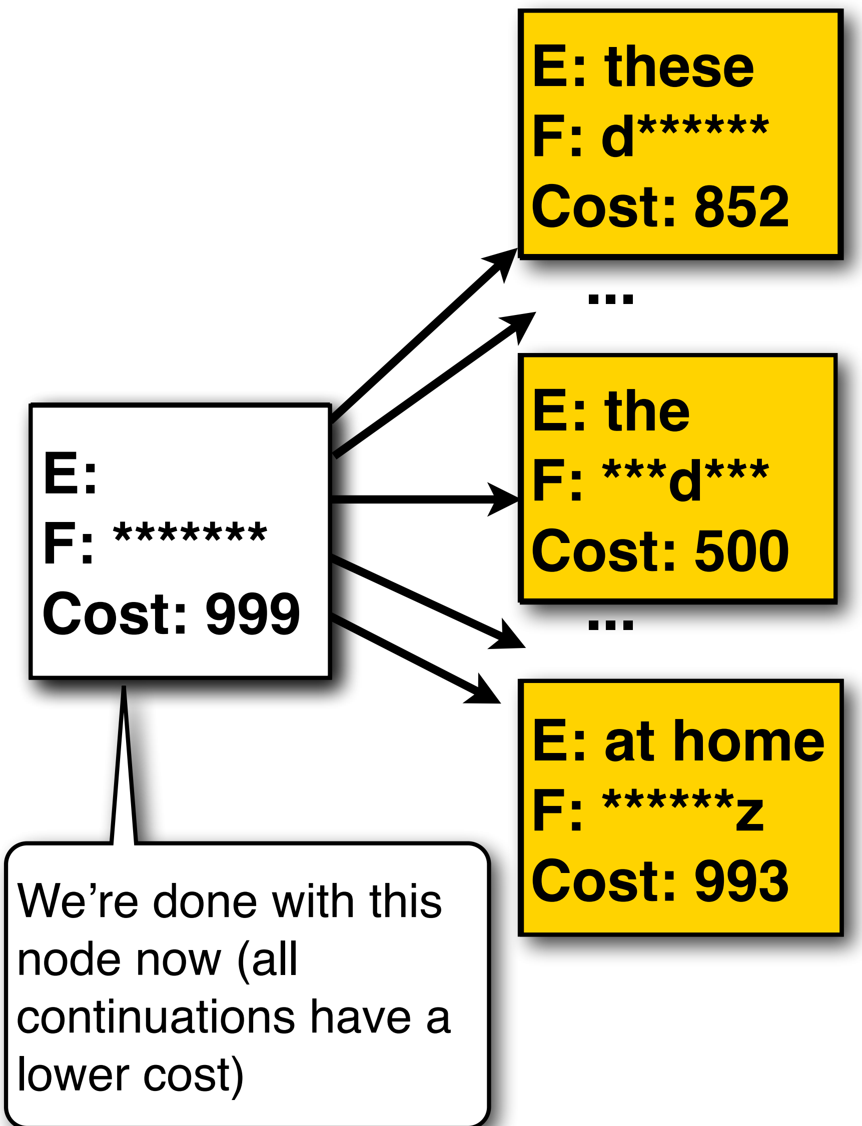
—**Close** the best open hypothesis.

Additional Pruning (*n*-best / beam search):
Only keep the *n* best open hypotheses around

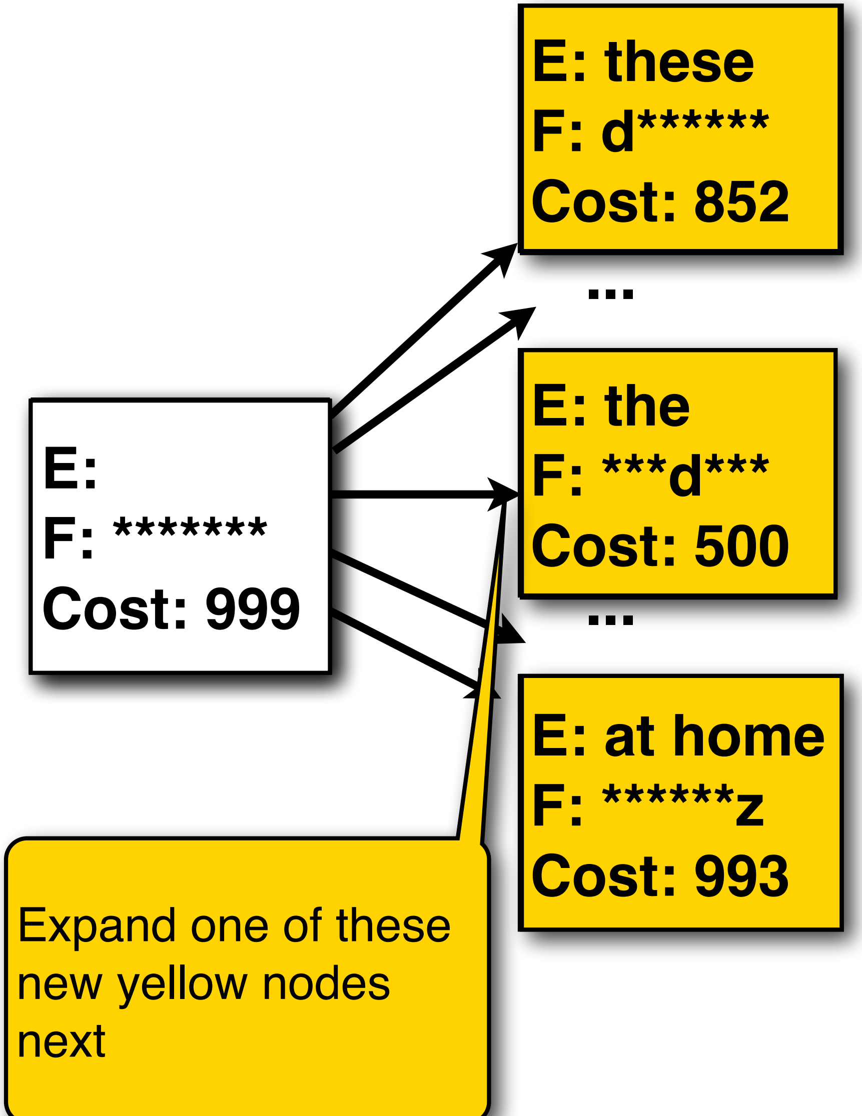
Stack-based decoding



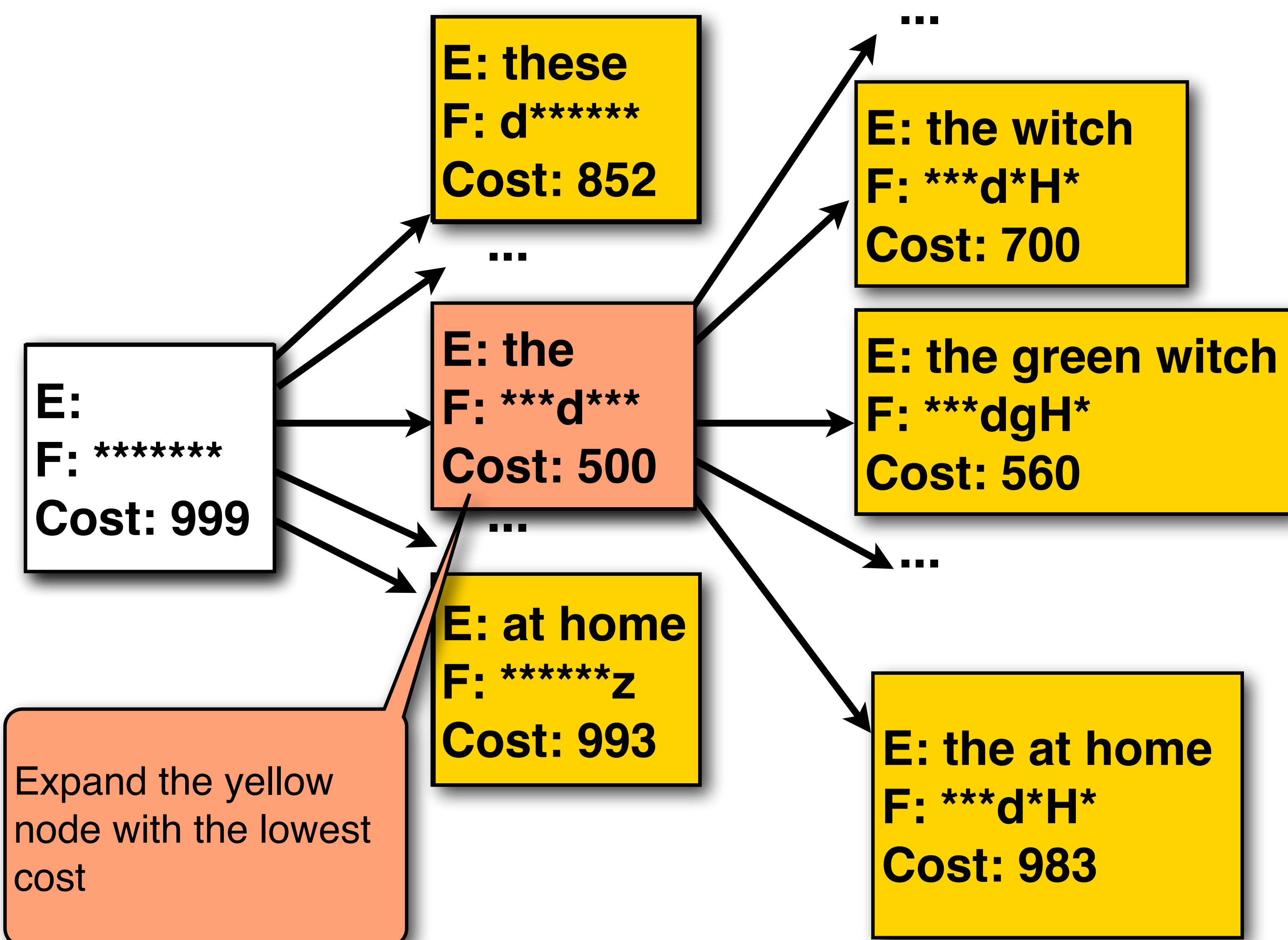
Stack-based decoding



Stack-based decoding



Stack-based decoding



Stack-based decoding