# Natural Language Processing CSE 325/425



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#### Lecture 25:

- Decoding of machine translation
- Neural translation via seq2seq models

- We have describe two alignment models
  - o IBM Model-1  $P(F,A|E) = P(J|I) \times \prod_{j=1}^{J} P(a_j|a_{j-1},I) P(f_j|e_{a_j}) \qquad (from EM)$
- How to find the best translation E given a foreign sentence F and the model:

translation model language model 
$$\hat{E} = \underset{E \in \text{English}}{\operatorname{argmax}} \underbrace{P(F|E)}_{\text{liven}} \underbrace{P(E)}$$

- Note that E is unknown and it is different from aligning E and F.
- Decoding with a bigram language model is NP-complete (Knight 1999).

- Need greedy heuristic search algorithms.
  - Believe that greedy is sufficient to find good quality translations.

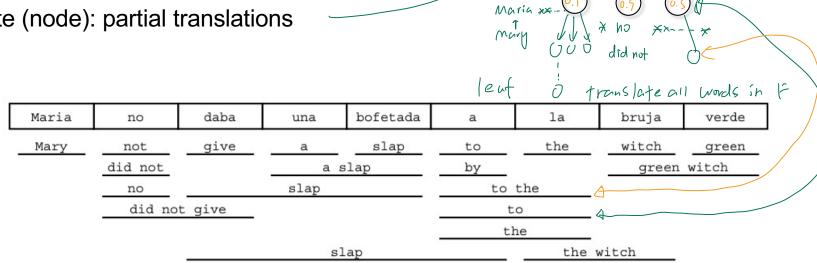


Best-first search

F

Partial translations

state (node): partial translations



Search Space

- Best-first search
  - state (node): partial translations
  - expansion (edge): translating one more word/phrase from previous states
  - expand the "best" state

measured in partial translation probability

$$P(E_{\mathrm{Partial}}) = \prod_{i \in \mathrm{Partial}} \phi(\bar{f}_i, \bar{e}_i) d(a_i - b_{i-1})$$
 $f_i \in \mathrm{Partial}$ 
 $f_i \in \mathrm{Partial}$ 

expensive: maintains many states

local maximum: good beginning but poor overall quality

when stop brith loca

a loof node with

the trighest perob

compared to all states

in the priority quebe.

Priority
Coffer the second
Oxpansion

bofetada

e: Mary

p: .534

e: witch

p: .182

expanded

bruja

e: Mary did not

e: Mary slap

p: .043

verde

(AI LONFSE)

 $\frac{O}{A} = \frac{1}{2} \left( \frac{1}{2} \right) = \frac{1}{2} \left( \frac{1}{2}$ HMM/model-1  $\neq$  http) =  $\overline{11}$   $\phi$  ( $\overline{f}_i$ ,  $\overline{e}_i^*$ )

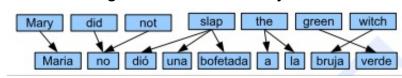
Use a function to evaluate both current and future quality.

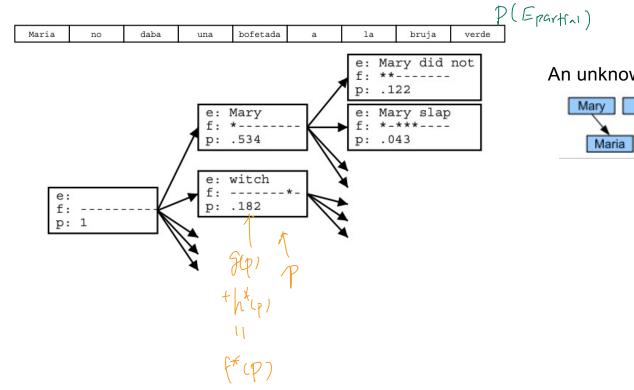
The quality of the partial translation

 $f^*(p) = g(p) + h^*(p)$  best possible translation quality for the yet-to-translate foreign words: expensive to estimate and needs heuristic.



An unknown good translation for your reference





Beam search (combined with best-first
or AX searches)

Computer vision o Beam = a small set of the current best states.

out down the # of states

That have to be leept in

Expand those states in the beam and only keep the best expansions. memory

Example: beam size = 2

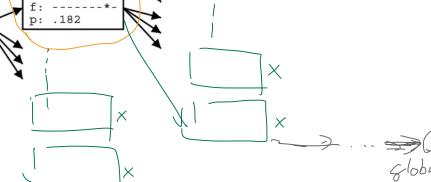
after the expansion, only keep the two best states

Beam (2) after the second expansion, again only keep the best two states. Benn [1] less memory size requirement; e: Mary did not

can have local minima;

combined with A\* heuristic. Learn [ 3]

e: Mary e: Mary slap p: .534 e: witch p: .182





- A Priority Evene
- Multi-stack search

$$\phi \quad P(Pattial) = 1$$
Maria + Mary P( ) = 0.524

$$x \times x - - x \quad P( ) = 0.0000$$

Translation of different number of foreign words can't be compared directly.

$$P(E_{ ext{Partial}}) = \prod_{i \in ext{Partial}} \phi(ar{f}_i, ar{e}_i) d(a_i - b_{i-1})$$
 in best -first secret

translations

1 Foreign Pharse

covering

- The more words/phases translated, the smaller the probability.
- Need a stack (priority queue) for each number of foreign words translated.

nf : # of foreign phases in F

```
hypothesis (>) Partial translation
initialize hypothesisStack[0 .. nf];
create initial hypothesis hyp_init;
add to stack hypothesisStack[0];
for i=0 to nf-1:
 for each hyp in hypothesisStack[i]:
    for each new_hyp that can be derived from hyp:
\longrightarrow nf[new_hyp] = number of foreign words covered by new_hyp; \phi
      add new_hyp to hypothesisStack[nf[new_hyp]];
      prune hypothesisStack[nf[new_hyp]];
find best hypothesis best_hyp in hypothesisStack[nf];
output best path that leads to best_hyp;
```

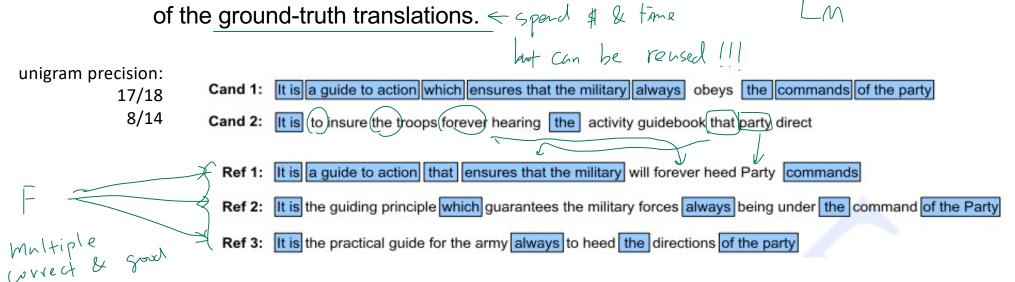
pointing to

#### **Evaluation**

- Human evaluation

  faithfolness

  fluency --
  Yeused !!!
- Automatic evaluation using BLEU score
  - Intuition: compute how often a predicted translation matches n-grams in any



BLEU: a method for automatic evaluation of machine translation, ACL, 2002

<u>Caution of using BLEU: https://slator.com/technology/how-bleu-measures-translation-and-why-it-matters/</u>

bi- Sram Precision?

#### **Evaluation**

 Compute precision for n-grams, for n=1,2,3,4 for all candidate translations predicted by the model.

$$\operatorname{prec}_{n} = \frac{\sum_{C \in \{Candidates\}} \sum_{n-gram \in C} \operatorname{Count}_{\operatorname{match}}(n - gram)}{\sum_{C' \in \{Candidates\}} \sum_{n-gram' \in C'} \operatorname{Count}(n - gram')}$$

• Then take the geometric mean of these precisions  $\left(\prod_{n=1}^4 \operatorname{prec}_n\right)^{\frac{1}{4}}$  as the BLEU score of translating a sentence

#### **Evaluation**

- Pitfalls in the evaluation using BLEU
  - Very short translations can have high precisions.

Very short translations can have high precisions. BLEU = penalty of brevity Example: "for the" will have precision 1 when the references contains the  $\frac{71}{r}$  Prec) 1/4 "for the", regardless of the remaining words.

Ref 3: It is the practical guide for the army always to heed the directions of the party

- Repetitive matches
  - Translation: "the the the the the the"

 $Precision_{n=1} = = 7/7$ 

- Reference: (the cat is on the mat"
- Modified precision should be just 2/7 (2 = max number of "the" in the reference)