Tuning

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28 September 2017

The Story so Far: Generative Models

- The definition of translation probability follows a mathematical derivation

$$\text{argmax}_{\mathbf{e}} p(\mathbf{e}|\mathbf{f}) = \text{argmax}_{\mathbf{e}} p(\mathbf{f}|\mathbf{e})\ p(\mathbf{e})$$

- Occasionally, some independence assumptions are thrown in
for instance IBM Model 1: word translations are independent of each other

$$p(\mathbf{e}|\mathbf{f}, a) = \frac{1}{Z} \prod_i p(e_i | f_{a(i)})$$

- Generative story leads to straight-forward estimation
  - maximum likelihood estimation of component probability distribution
  - EM algorithm for discovering hidden variables (alignment)

Log-linear Models

- IBM Models provided mathematical justification for multiplying components

$$p_{LM} \times p_{TM} \times p_D$$

- These may be weighted

$$p_{LM}^{\lambda_{LM}} \times p_{TM}^{\lambda_{TM}} \times p_D^{\lambda_D}$$

- Many components p_i with weights λ_i

$$\prod_i p_i^{\lambda_i}$$

- We typically operate in log space

$$\sum_i \lambda_i \log(p_i) = \log \prod_i p_i^{\lambda_i}$$

Knowledge Sources

- Many different knowledge sources useful
  - language model
  - reordering (distortion) model
  - phrase translation model
  - word translation model
  - word count
  - phrase count
  - character count
  - drop word feature
  - phrase pair frequency
  - additional language models
- Could be any function $h(\mathbf{e}, \mathbf{f}, \mathbf{a})$

$$h(\mathbf{e}, \mathbf{f}, \mathbf{a}) = \begin{cases} 1 & \text{if } \exists e_i \in \mathbf{e}, e_i \text{ is verb} \\ 0 & otherwise \end{cases}$$

Set Feature Weights

- Contribution of components p_i determined by weight λ_i

- Methods
  - manual setting of weights: try a few, take best
  - automate this process

- Learn weights
  - set aside a development corpus
  - set the weights, so that optimal translation performance on this development corpus is achieved
  - requires automatic scoring method (e.g., BLEU)

Discriminative vs. Generative Models

- Generative models
  - translation process is broken down to steps
  - each step is modeled by a probability distribution
  - each probability distribution is estimated from data by maximum likelihood
- Discriminative models
  - model consist of a number of features (e.g. the language model score)
  - each feature has a weight, measuring its value for judging a translation as correct
  - feature weights are optimized on development data, so that the system output matches correct translations as close as possible

Overview

- Generate a set of possible translations of a sentence (candidate translations)
- Each candidate translation represented using a set of features
- Each feature derives from one property of the translation
  - feature score: value of the property
    (e.g., language model probability)
  - feature weight: importance of the feature
    (e.g., language model feature more important than word count feature)
- Task of discriminative training: find good feature weights
- Highest scoring candidate is best translation according to model

Discriminative Training Approaches

- Reranking: 2 pass approach
  - first pass: run decoder to generate set of candidate translations
  - second pass:
    * add features
    * rescore translations

- Tuning
  - integrate all features into the decoder
  - learn feature weights that lead decoder to best translation

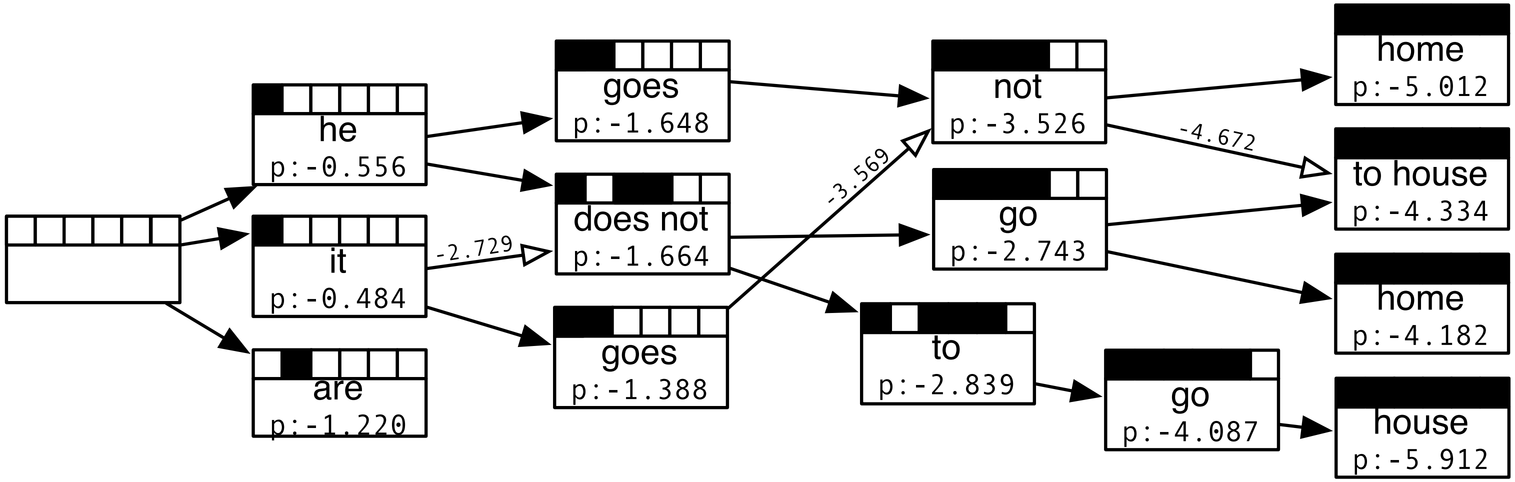
- Large scale discriminative training (next lecture)
  - thousands or millions of features
  - optimization of the entire training corpus
  - requires different training methods

finding candidate translations

Finding Candidate Translations

- Number of possible translations exponential with sentence length
- But: we are mainly interested in the most likely ones
- Recall: decoding
  - do not list all possible translation
  - beam search for best one
  - dynamic programming and pruning
- How can we find **set** of best translations?

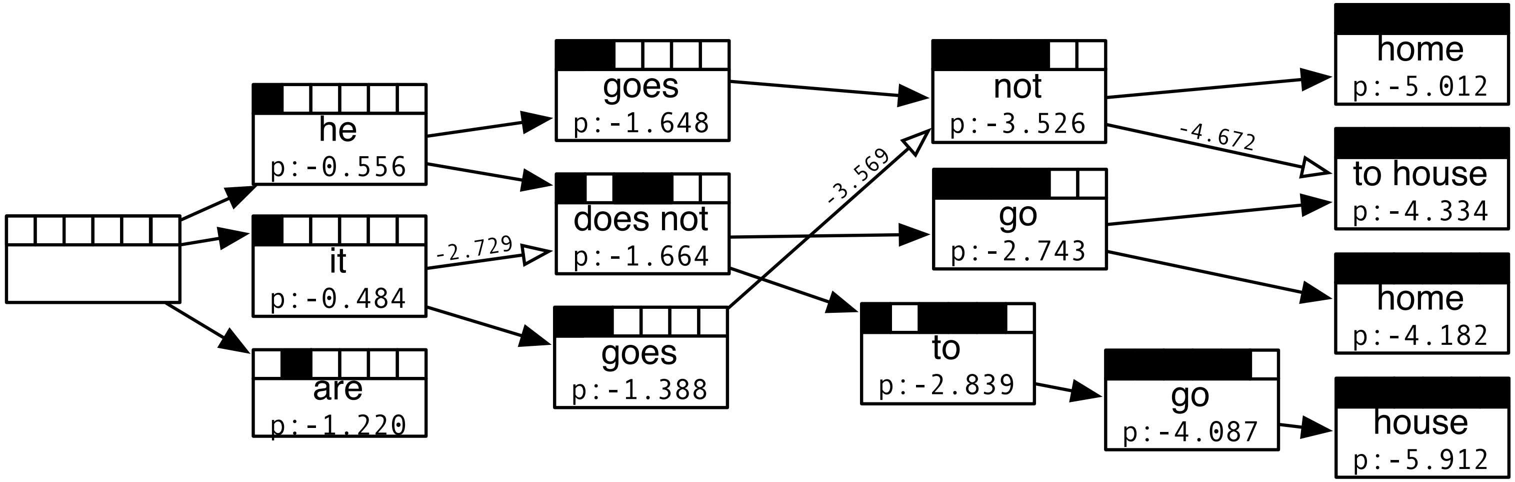
Search Graph



- Decoding explores space of possible translations
  by expanding the most promising partial translations

⇒ Search graph

Search Graph

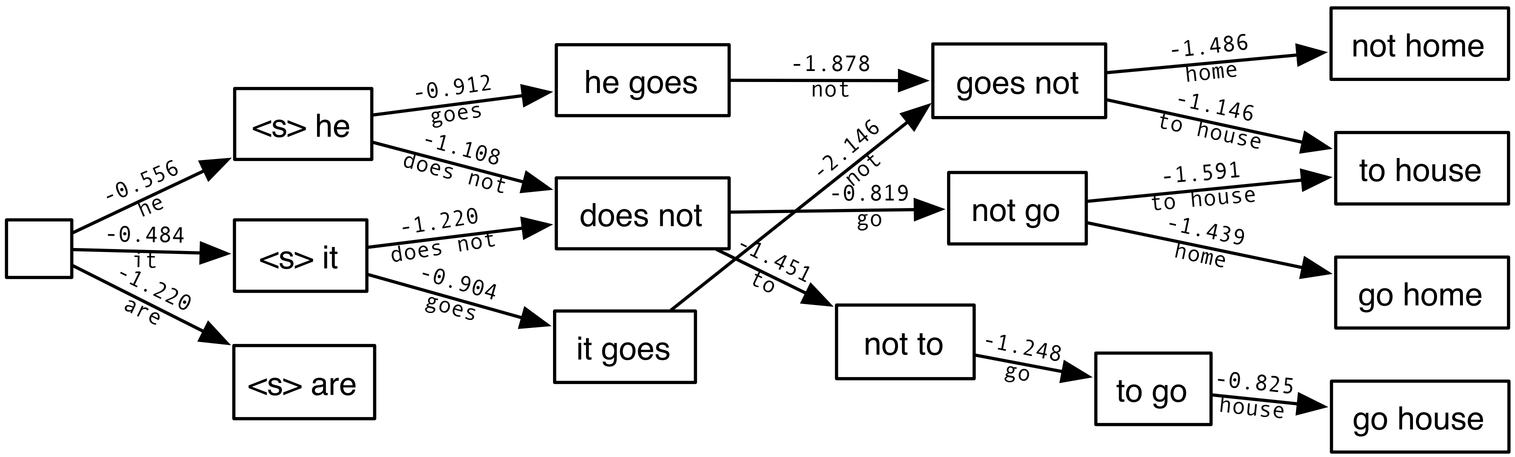


- Keep transitions from recombinations
  - without: total number of paths = number of full translation hypotheses
  - with: combinatorial expansion

- Example
  - without: 4 full translation hypotheses
  - with: 10 different full paths

- Typically many more paths due to recombination

Word Lattice



- Search graph as finite state machine
  - states: partial translations
  - transitions: applications of phrase translations
  - weights: added scores by phrase translation

Finite State Machine

- Formally, a finite state machine, is a q quintuple $(\Sigma, S, s_0, \delta, F)$, where
  - Σ is the alphabet of output symbols (in our case, the emitted phrases)
  - S is a finite set of states
  - s_0 is an initial state ($s_0 \in S$), (in our case the initial hypothesis)
  - δ is the state transition function $\delta : S \times \Sigma \rightarrow S$
  - F is the set of final states (in our case representing hypotheses that have covered all input words).

- Weighted finite state machine
  - scores for emissions from each transition $\pi : S \times \Sigma \times S \rightarrow \mathbf{R}$

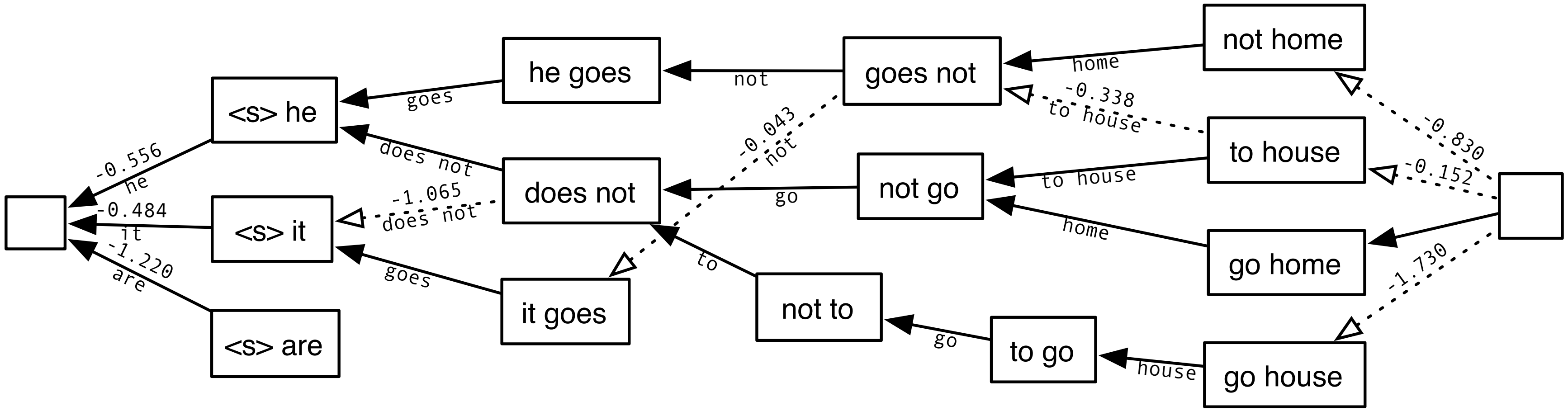
N-Best List

rank	score	sentence
1	-4.182	he does not go home
2	-4.334	he does not go to house
3	-4.672	he goes not to house
4	-4.715	it goes not to house
5	-5.012	he goes not home
6	-5.055	it goes not home
7	-5.247	it does not go home
8	-5.399	it does not go to house
9	-5.912	he does not to go house
10	-6.977	it does not to go house

- Word graph may be too complex for some methods

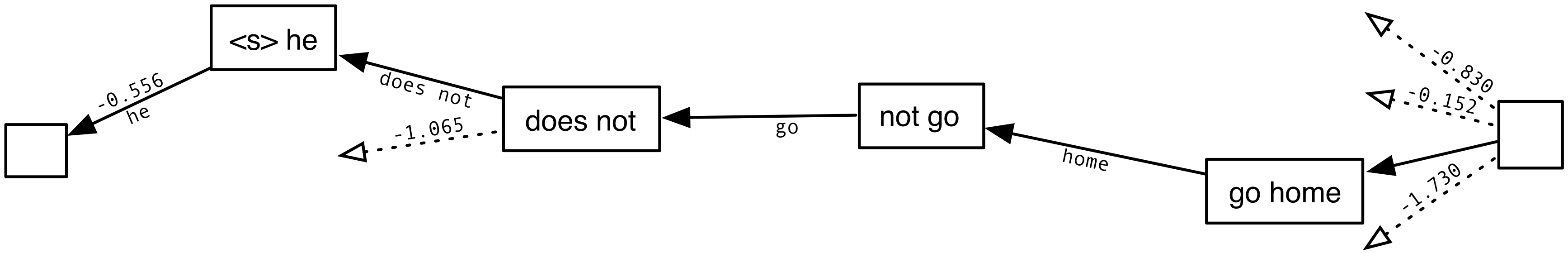
$\Rightarrow$ Extract n best translations

Computing N-Best Lists



- Representing the graph with back transitions
- Include ”detours” with cost

Path 1



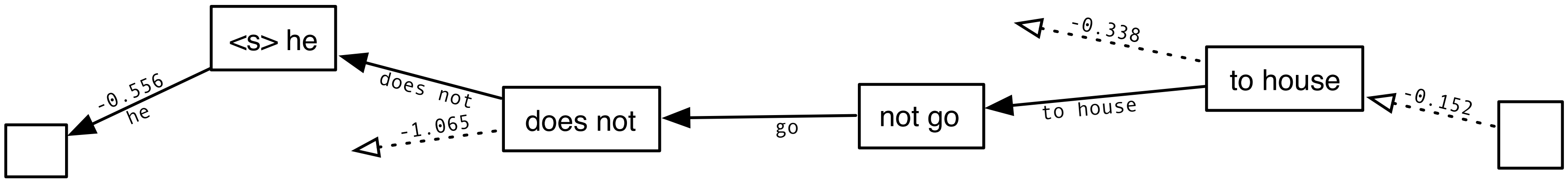
- Follow back transitions

⇒ Best path: he does not go home

- Keep note of detours from this path

Base path	**Base cost**	**Detour cost**	**Detour state**
final	-0	-0.152	to house
final	-0	-0.830	not home
final	-0	-1.065	does not
final	-0	-1.730	go house

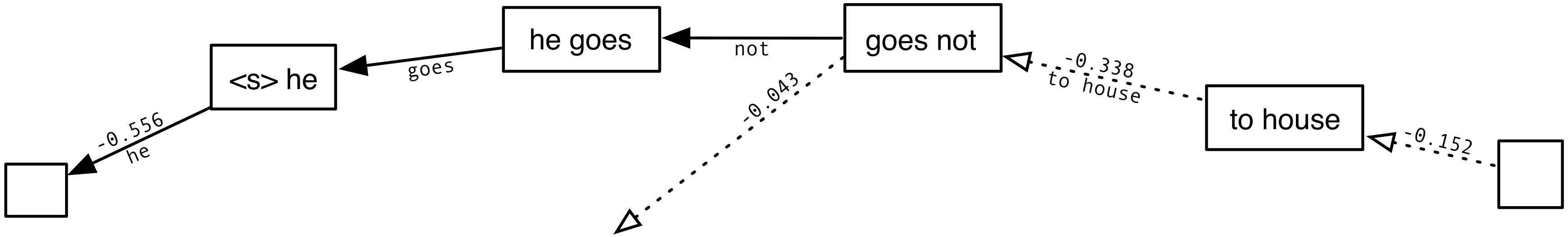
Path 2



- Take cheapest detour
- Afterwards, follow back transitions
- Second best path: he does not go to house
- Add its detours to priority queue

Base path	Base cost	Detour cost	Detour state
to house	-0.152	-0.338	goes not
final	-0	-0.830	not home
final	-0	-1.065	does not
to house	-0.152	-1.065	it
final	-0	-1.730	go house

Path 3



- Third best path: he goes not to house
- Add its detours to priority queue

Base path	Base cost	Detour cost	Detour state
to house / goes not	-0.490	-0.043	it goes
final	-0	-0.830	not home
final	-0	-1.065	does not
to house	-0.152	-1.065	it
final	-0	-1.730	go house

Scoring N-Best List

- Two opinions about items in the n-best list
  - model score: what the machine translation system thinks is good
  - error score: what is actually a good translation
- Error score can be computed with reference translation
  - recall: lecture on evaluation
  - canonical metric: BLEU score
- Some methods require sentence-level scores
  - commonly used: BLEU+1
  - adjusted precision: $\frac{\text{correct matches}+1}{total+1}$

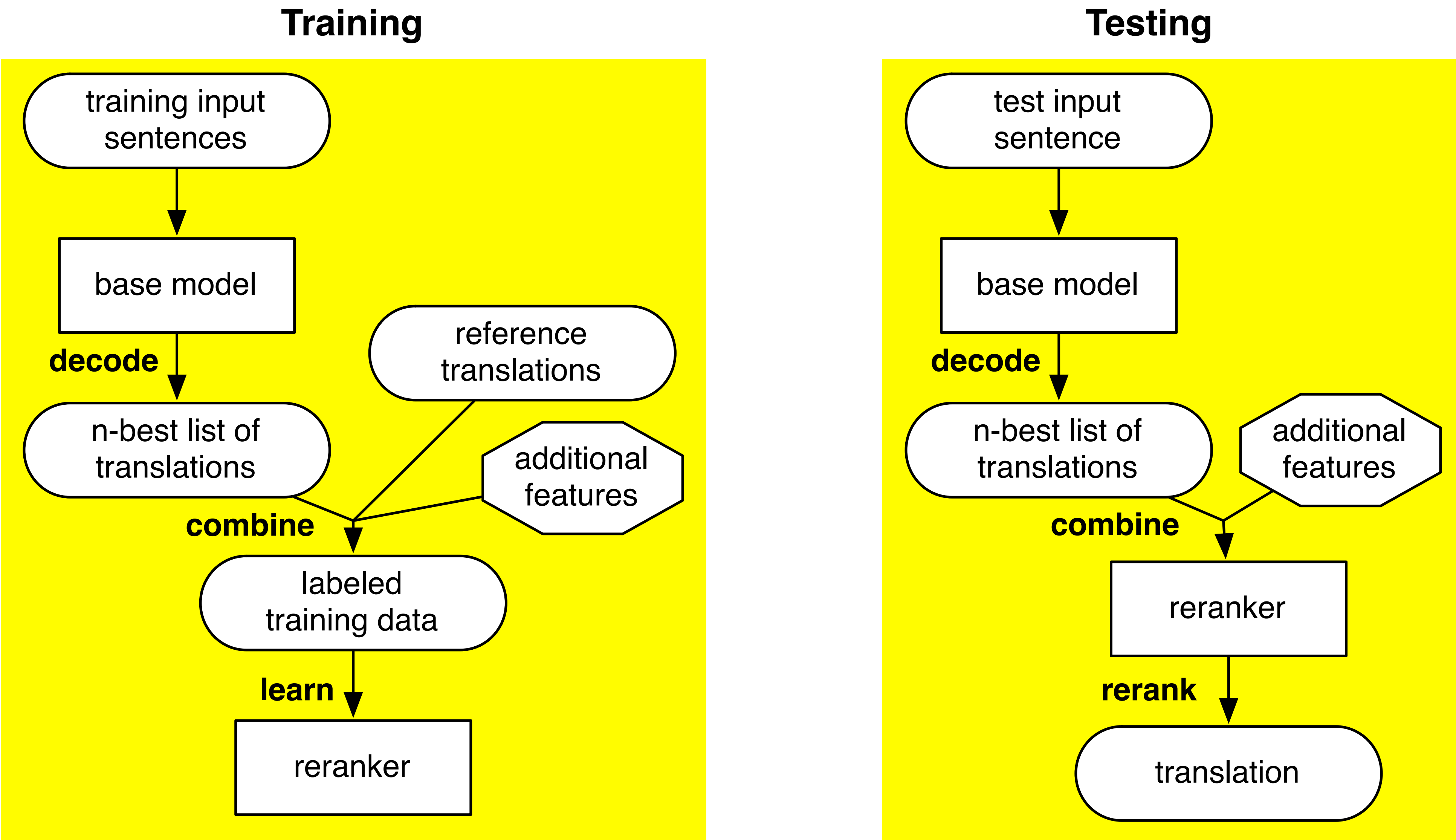
Scored N-Best List

- Reference translation: he does not go home
- N-best list

Translation	Feature values						BLEU+1
it is not under house	-32.22	-9.93	-19.00	-5.08	-8.22	-5	27.3%
he is not under house	-34.50	-7.40	-16.33	-5.01	-8.15	-5	30.2%
it is not a home	-28.49	-12.74	-19.29	-3.74	-8.42	-5	30.2%
it is not to go home	-32.53	-10.34	-20.87	-4.38	-13.11	-6	31.2%
it is not for house	-31.75	-17.25	-20.43	-4.90	-6.90	-5	27.3%
he is not to go home	-35.79	-10.95	-18.20	-4.85	-13.04	-6	31.2%
he does not home	-32.64	-11.84	-16.98	-3.67	-8.76	-4	**36.2%**
it is not packing	-32.26	-10.63	-17.65	-5.08	-9.89	-4	21.8%
he is not packing	-34.55	-8.10	-14.98	-5.01	-9.82	-4	24.2%
he is not for home	-36.70	-13.52	-17.09	-6.22	-7.82	-5	32.5%

- What feature weights push up the correct translation?

Rerank Approach



parameter tuning

Parameter Tuning

- Recall log-linear model

$$p(x) = \exp \sum_{i=1}^{n} \lambda_i h_i(x)$$

- Overall translation score $p(x)$ is combination of components $h_i(x)$, weighted by parameters λ_i

- Setting parameters as supervised learning problem

- Two methods
  - Powell search
  - Simplex algorithm

Experimental Setup

- Training data for translation model: 10s to 100s of millions of words
- Training data for language model: billions of words
- Parameter tuning
  - set a few weights (say, 10–15)
  - tuning set of 1000s of sentence pairs sufficient
- Finally, test set needed

Minimum Error Rate Training

- Optimize metric: e.g., BLEU
- Tuning set of 1000s of sentences,
  for each we have n-best list of translations
- Different weight setting
  $\rightarrow$ different translations come out on top
  $\rightarrow$ BLEU score
- Even with 10-15 features: high dimensional space, intractable

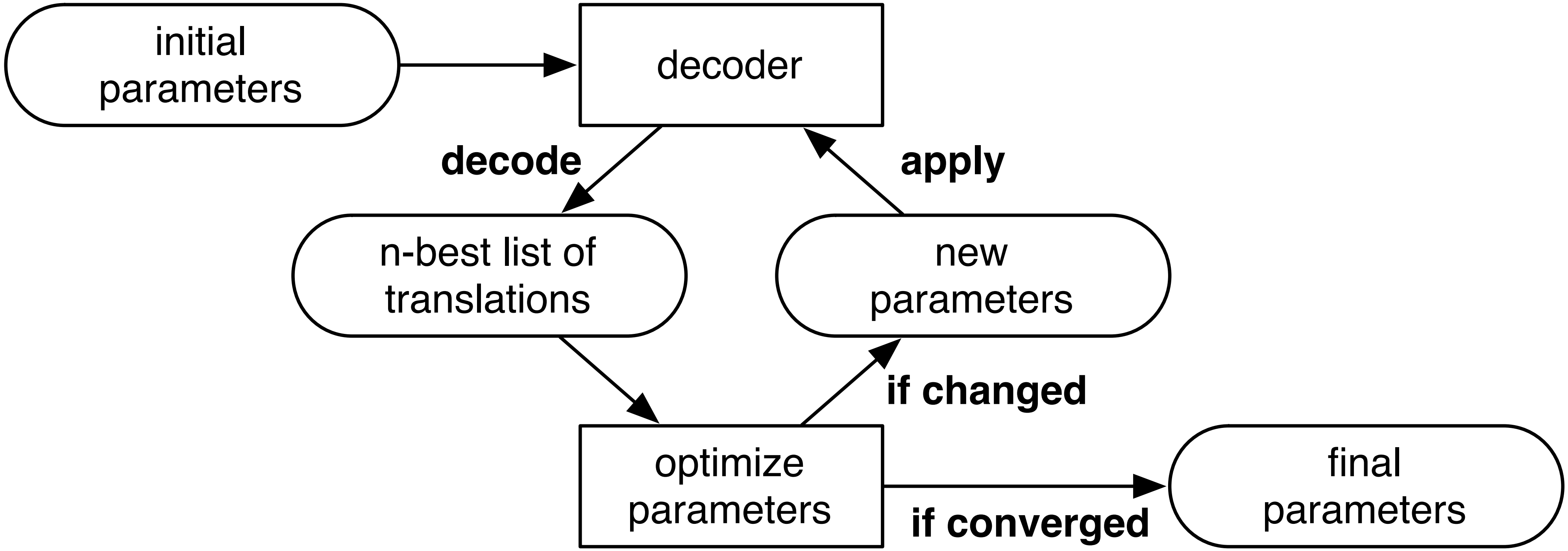
Bad N-Best Lists?

- N-Best list produced with initial weight setting

- Decoding with optimized weight settings
  $\rightarrow$ may produce completely different translations

$\Rightarrow$ Iterate optimization, accumulate n-best lists

Parameter Tuning



powell search

Och's minimum error rate training (MERT)

- Line search for best feature weights

```
given: sentences with n-best list of
translations
iterate n times
    randomize starting feature weights
        iterate until convergences
            for each feature
                find best feature weight
                update if different from
current
return best feature weights found in any
iteration
```

Find Best Feature Weight

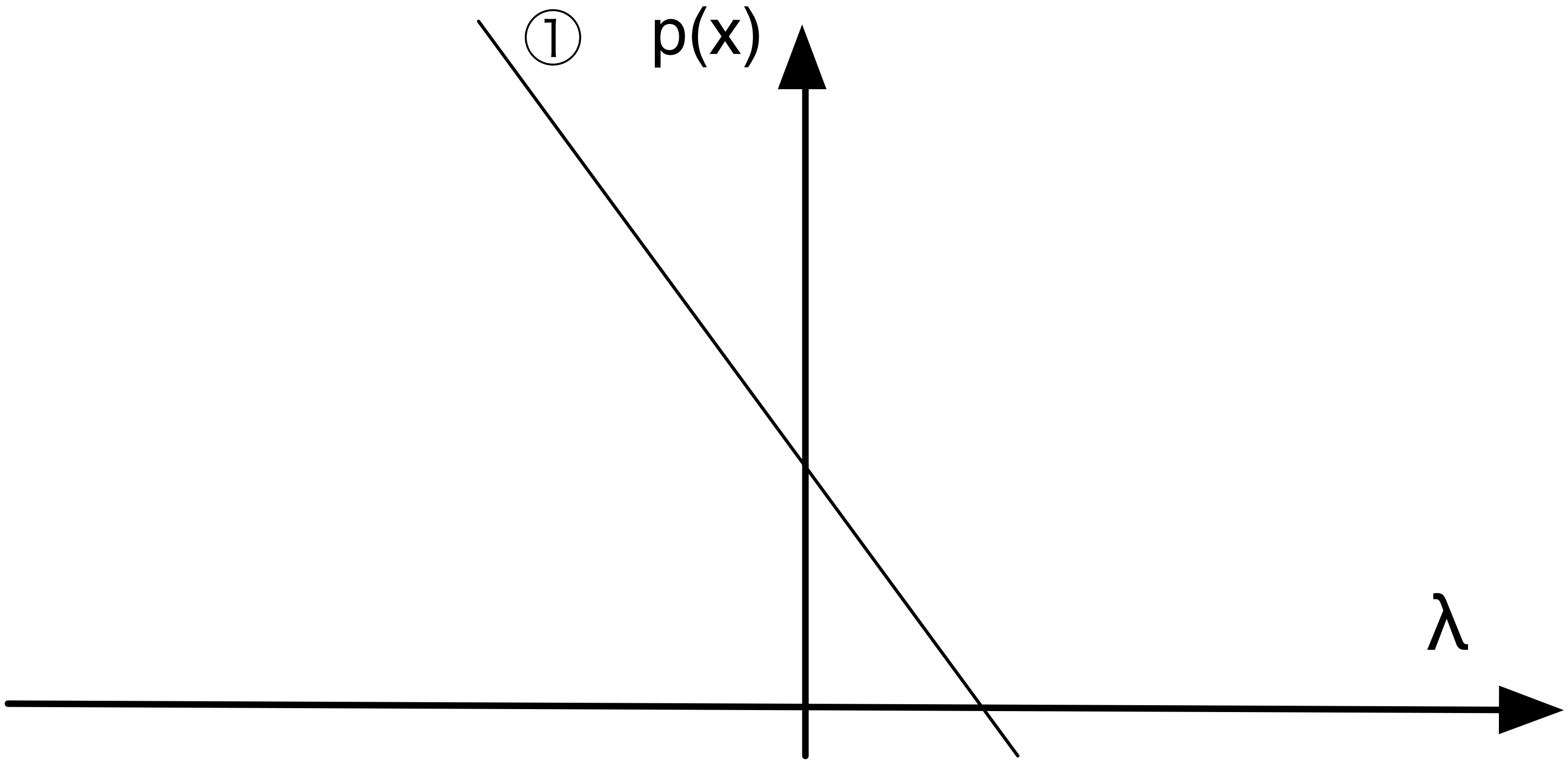
- Core task:
  - find optimal value for one parameter weight λ
  - ... while leaving all other weights constant

- Score of translation i for a sentence **f**:

$$p(\mathbf{e}_i|\mathbf{f}) = \lambda a_i + b_i$$

- Recall that:
  - we deal with 100s of translations $\mathbf{e}_i$ per sentence **f**
  - we deal with 100s or 1000s of sentences **f**
  - we are trying to find the value λ so that over all sentences, the error score is optimized

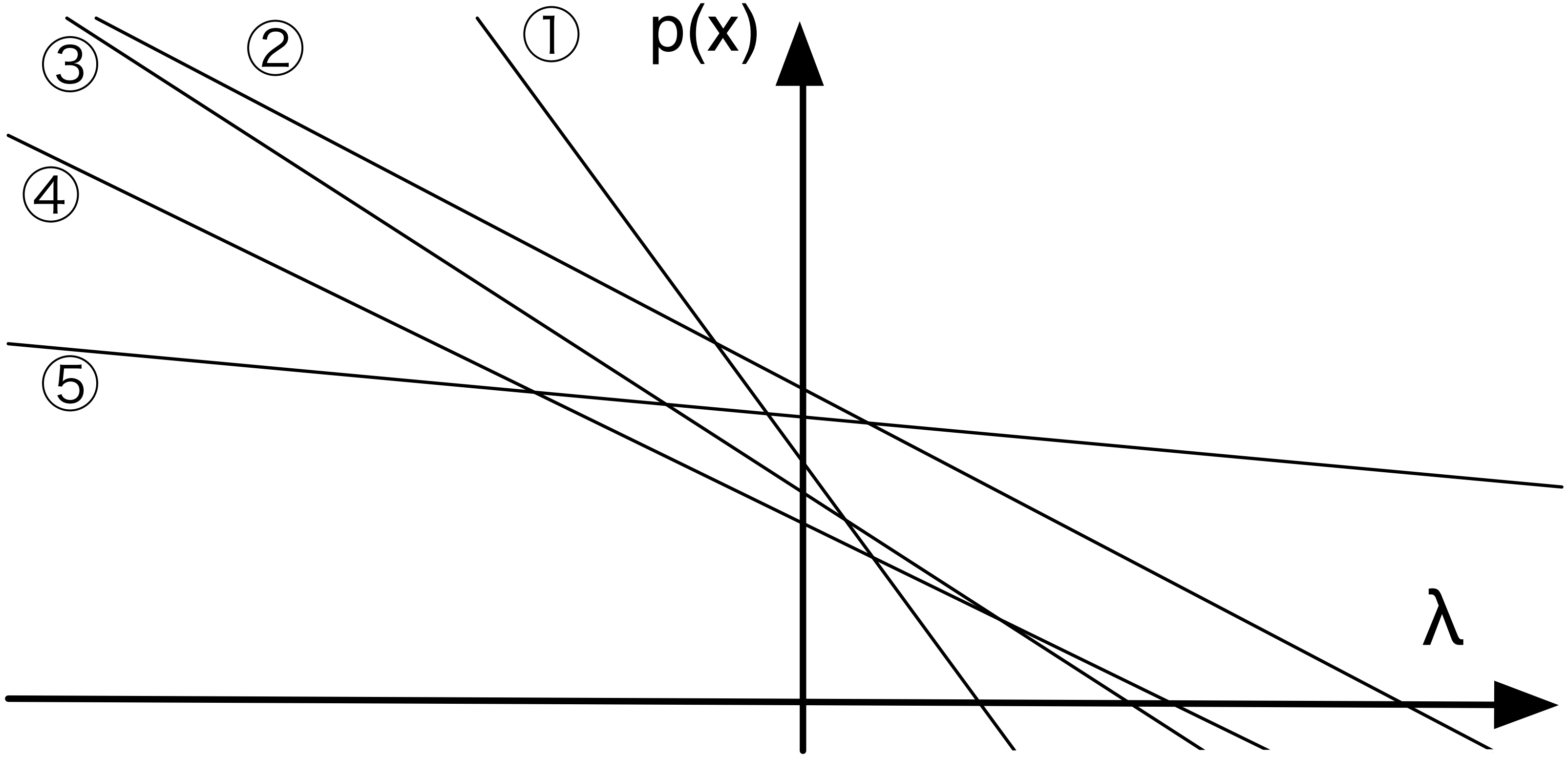
One Translations for One Sentence



- Probability of one translation $p(\mathbf{e}_i|\mathbf{f})$ is a function of λ

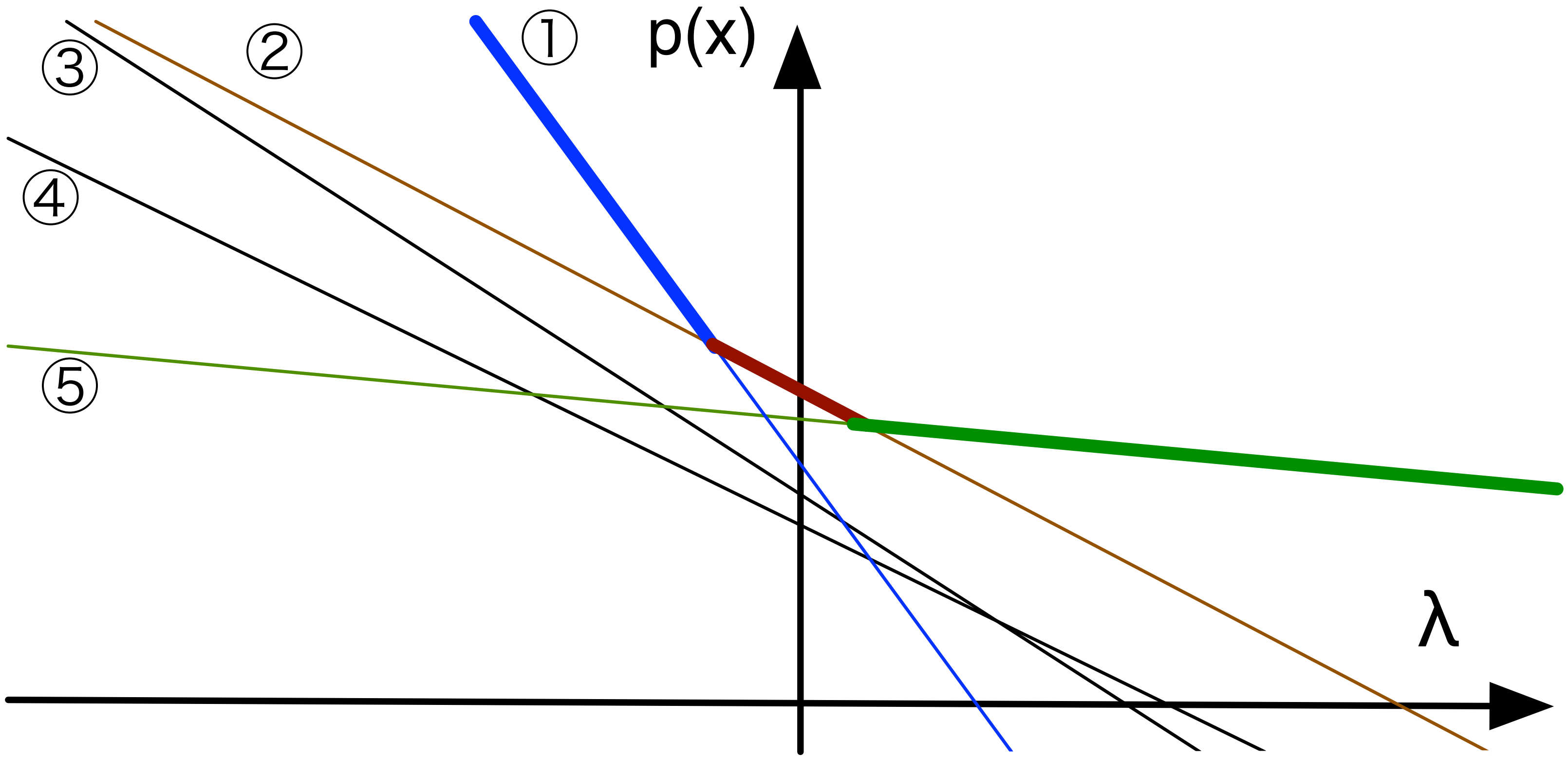
$$p(\mathbf{e}_i|\mathbf{f}) = \lambda a_i + b_i$$

N-Best Translations for One Sentence



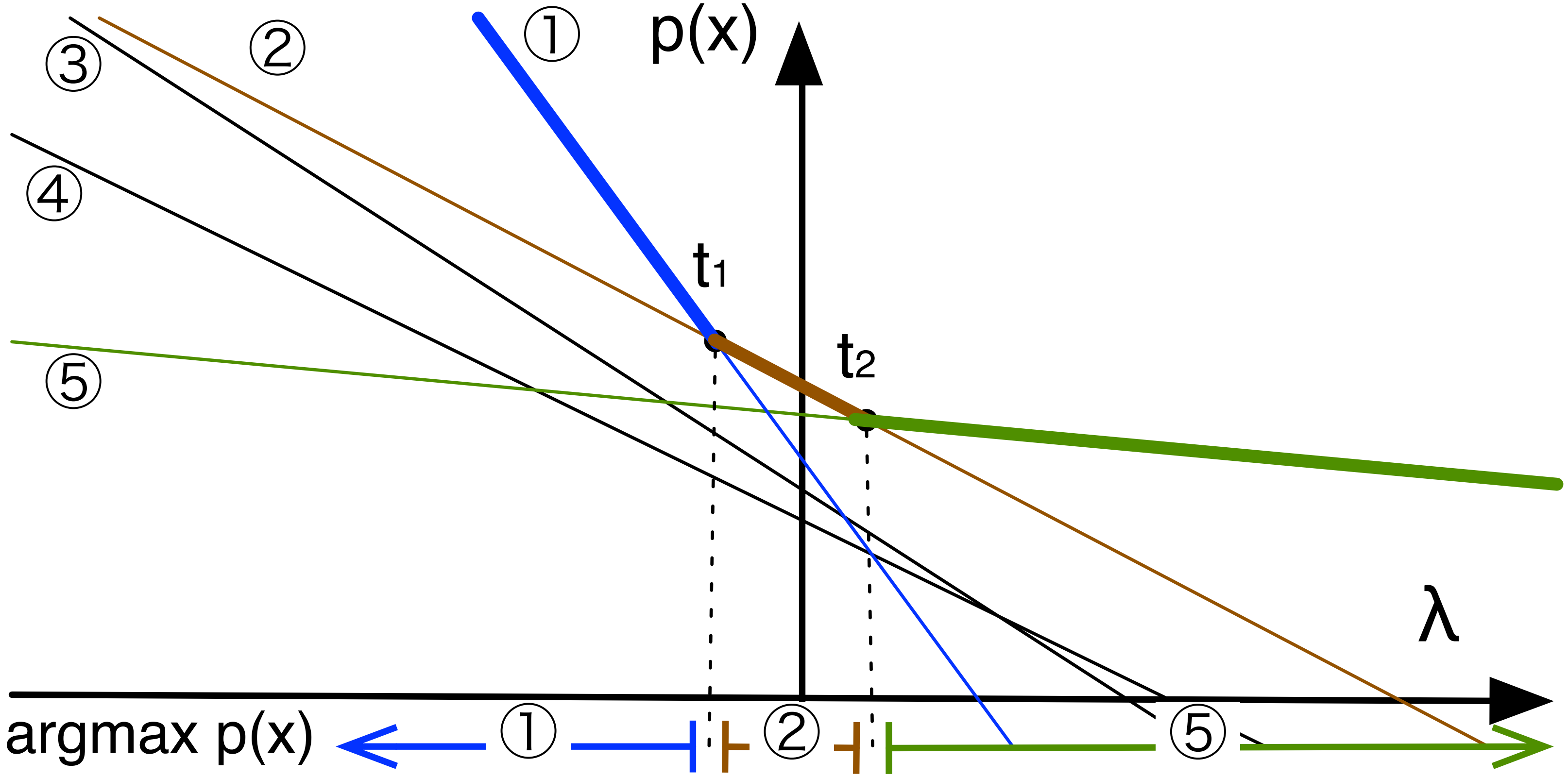
- Each translation is a different line

Upper Envelope



- Highest probability translation depends on λ

Threshold Points



- There are one a few threshold points t_j where the model-best line changes

Finding the Optimal Value for λ

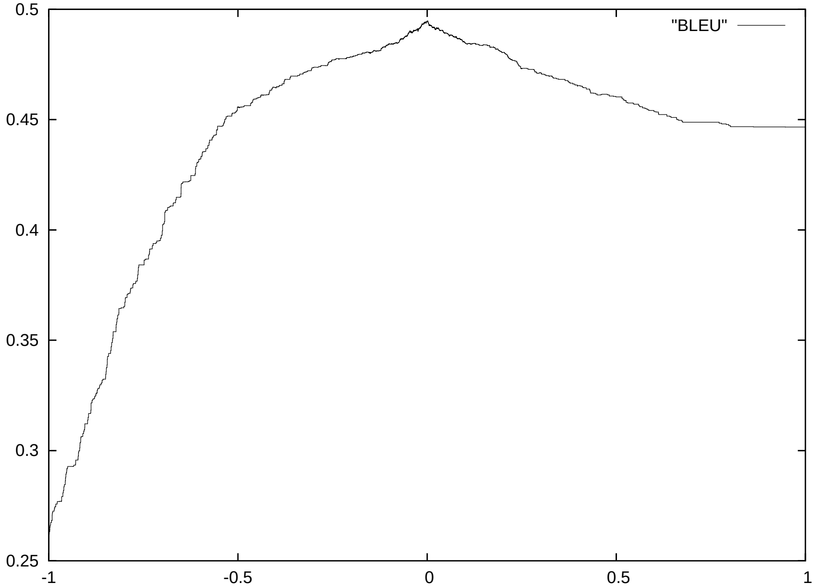
- Real-valued λ can have infinite number of values
- But only on threshold points, one of the model-best translation changes

$\Rightarrow$ Algorithm:

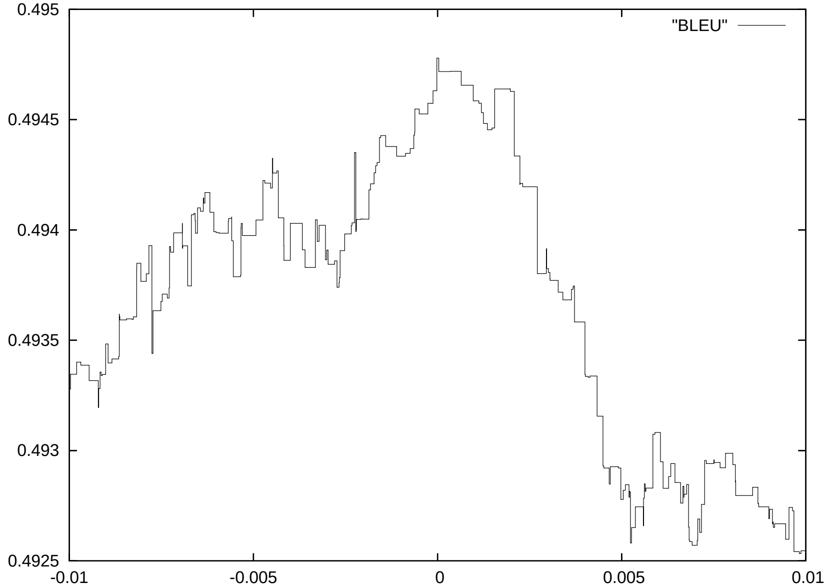
- find the threshold points
- for each interval between threshold points
  - find best translations
  - compute error-score
- pick interval with best error-score

BLEU Error Surface

- Varying one parameter: a rugged line with many local optima



full range



peak

Pseudo Code

Input: sentences with n-best list of translations, initial parameter values

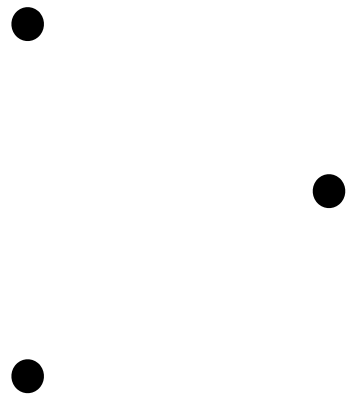
repeat
  for all parameter **do**
    set of threshold points $T = \{\}$
    for all sentence **do**
      for all translation **do**
        compute line l: parameter value $\rightarrow$ score
      end for
      find line l with steepest descent
      while find line l_2 that intersects with l first **do**
        add parameter value at intersection to set of threshold points T
        $l = l_2$
      end while
    end for
    sort set of threshold points T by parameter value
    compute score for value before first threshold point
    for all threshold point $t \in T$ **do**
      compute score for value after threshold point t
      if highest **do** record max score and threshold point t
    end for
    if max score is higher than current **do** update parameter value
  end for
until no changes to parameter values applied

simplex algorithm

Simplex Algorithm

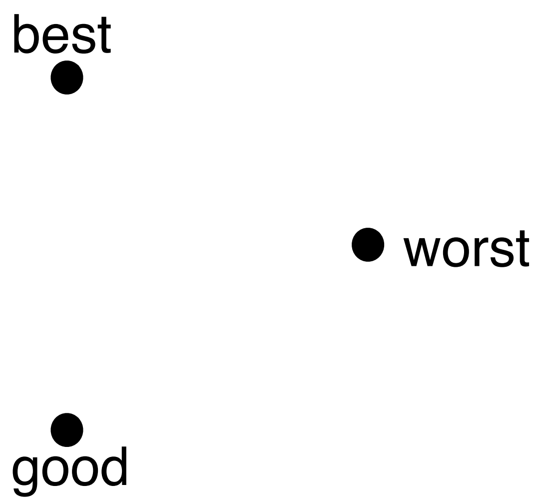
- Similar to Powell search
- Less calculations of the current error
  - recall: error is computed over the entire tuning set
  - brute force method requires reranking of 1000s of n-best lists
- Similar to gradient descent methods
  - try to find direction in which the optimum lies
  - here: we cannot compute derivative

Simplex Algorithm



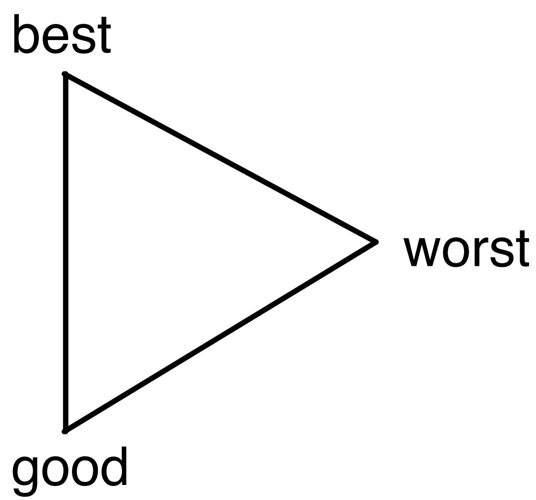
- Randomly generate three points in the high dimensional space
  - high dimensional space = each dimension is one of the λ_i parameters
  - a point in the space = each parameter set to a value

Simplex Algorithm



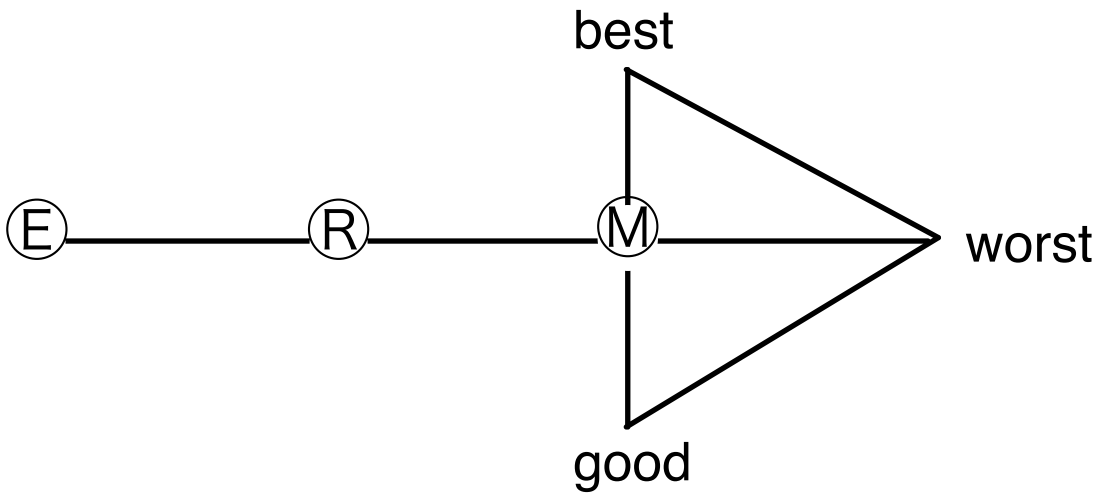
- We can score each of these points
  - use parameter settings to rerank all the n-best lists
  - compute overall tuning set score (BLEU)
- Rank the 3 points into best, good, worst

Simplex Algorithm



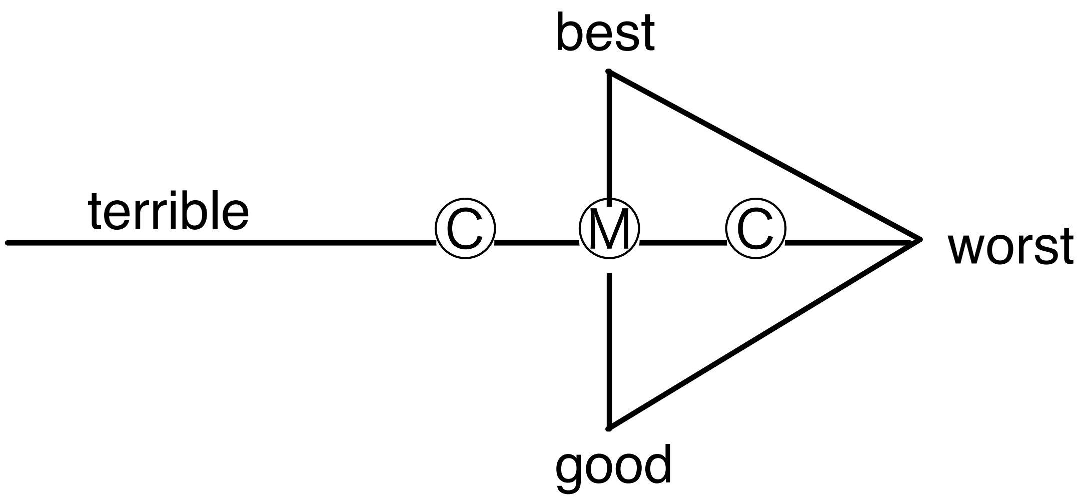
- The 3 points form a triangle

First Idea: Move Away from the Bad Point



- Compute 3 additional points
  - mid point: $M = \frac{1}{2}(\text{best} + \text{good})$
  - reflection point: $R = M + (M - \text{worst})$
  - extension: $R = M + 2(M - \text{worst})$
- Three cases
  1. if $\text{error}(E) < \text{error}(R) < \text{error}(\textit{worst})$, replace *worst* with E.
  2. else if $\text{error}(R) < \text{error}(\textit{worst})$, replace *worst* with R.
  3. else try something else

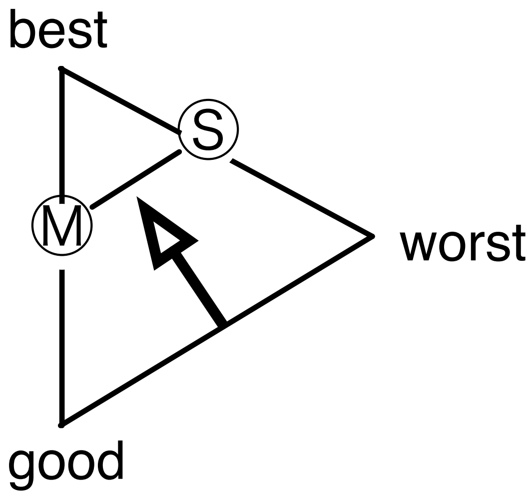
Second Idea: Well, Not Too Far Away



- Compute 2 additional points
  - C_1 point between *worst* and M: $C_1 = M + \frac{1}{2}(M - \textit{worst})$
  - C_2 point between M and R: $C_2 = M + \frac{3}{2}(M - \textit{worst})$.
- Three cases

1. if $\text{error}(C_1) < \text{error}(\textit{worst})$ and $\text{error}(C_1) < \text{error}(C_2)$, replace *worst* with C_1.
2. if $\text{error}(C_2) < \text{error}(\textit{worst})$ and $\text{error}(C_2) < \text{error}(C_1)$, replace *worst* with C_2.
3. else continue

Third Idea: Move Closer to Best Point



- Compute 1 additional point
  - S point between *worst* and *best*: $S = \frac{1}{2}(\textit{best} + \textit{worst})$.
- Shrink triangle

Simplex in High Dimensions

- Process of updates is iterated until the points converge

- Typically very quick

- More dimensions: more points
  - $n + 1$ points for n parameters
  - midpoint M is the center of all points except *worst*
  - in final case, all *good* points moved towards midpoints closer to *best*

- Once optimum is found
  - generate n-best list
  - iterate

Summary

- Reframing probabilistic model as log-linear model with weights
- Discriminative training task: set weights
- Generate n-best candidate translations from search graph
- Reranking
- Powell search (Och's MERT)
- Simplex algorithm