Statistical Machine Translation
Part V – Log-Linear Models

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Where we have been

- We have covered all bases!
- Solving a problem where we are predicting a structured output:
  - Problem definition
  - Evaluation, i.e., how will we evaluate progress?
  - Model
  - Training = parameter estimation
  - Search (= decoding, for SMT)

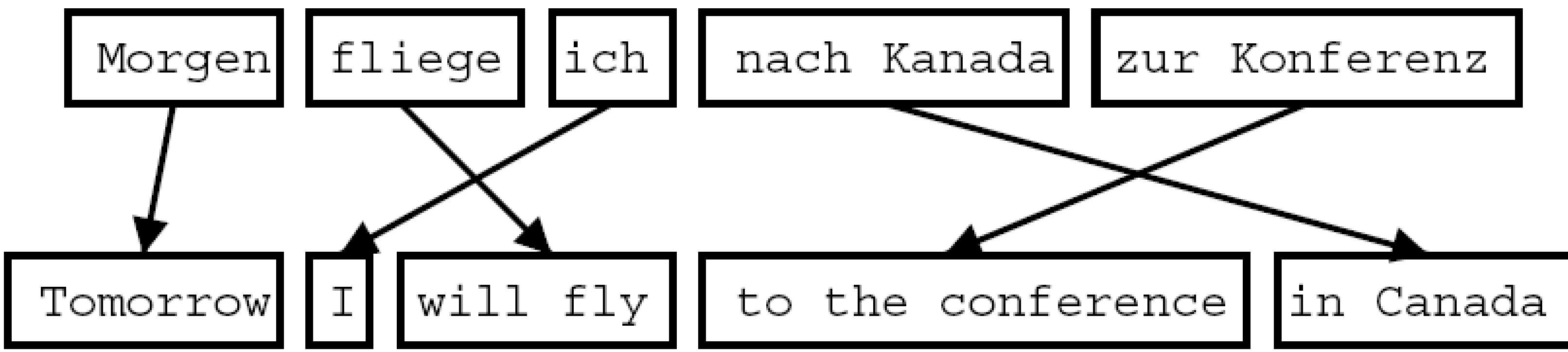
Where we are going

- The generative models we have seen so far are good, but we can do better
  - Switch to discriminative models (this will be defined later)
  - We will see that this frees us from the structure of the generative model!
    - We can concentrate on new knowledge sources
    - Also, no more annoying open parameters
  - The kind of model I will present is used practically everywhere in NLP these days

Outline

- Recap: original phrase-based model, search
- Optimizing parameters
- Deriving the log-linear model
- Tuning the log-linear model
- Adding new features

Phrase-based translation



- Foreign input is segmented in phrases
  - any sequence of words, not necessarily linguistically motivated
- Each phrase is translated into English
- Phrases are reordered

Slide from Koehn 2008

Phrase-based translation model

- Major components of phrase-based model
  - **phrase translation model** $\phi(\mathbf{f}|\mathbf{e})$
  - **reordering model** d
  - **language model** $p_{\text{LM}}(\mathbf{e})$
- Bayes rule

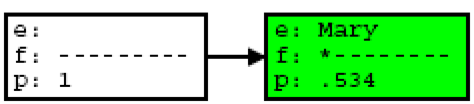
$$\begin{aligned} \text{argmax}_{\mathbf{e}} p(\mathbf{e}|\mathbf{f}) &= \text{argmax}_{\mathbf{e}} p(\mathbf{f}|\mathbf{e}) p(\mathbf{e}) \\ &= \text{argmax}_{\mathbf{e}} \phi(\mathbf{f}|\mathbf{e}) p_{\text{LM}}(\mathbf{e}) \omega^{\text{length}(\mathbf{e})} \end{aligned}$$

- Sentence $\mathbf{f}$ is decomposed into I phrases $\bar{f}_1^I = \bar{f}_1, ..., \bar{f}_I$
- Decomposition of $\phi(\mathbf{f}|\mathbf{e})$

$$\phi(\bar{f}_1^I|\bar{e}_1^I) = \prod_{i=1}^{I} \phi(\bar{f}_i|\bar{e}_i) d(a_i - b_{i-1})$$

Modified from Koehn 2008

Hypothesis Expansion



- Pick *translation option*
- Create *hypothesis*
  - e: add English phrase Mary
  - f: first foreign word covered
  - p: probability 0.534

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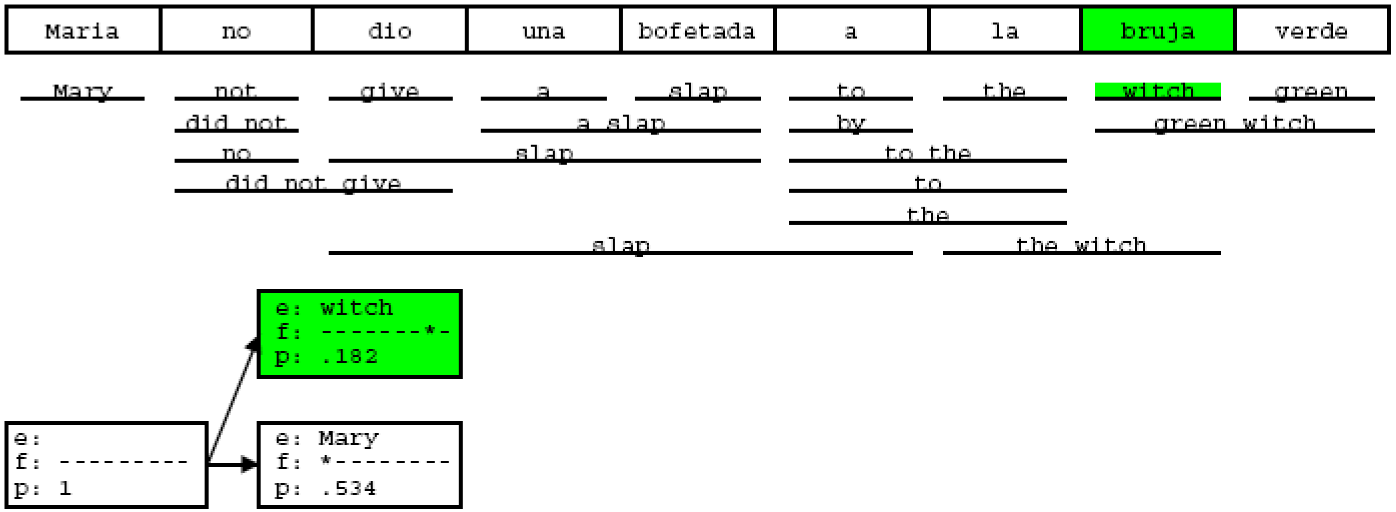
Hypothesis Expansion



- Add another *hypothesis*

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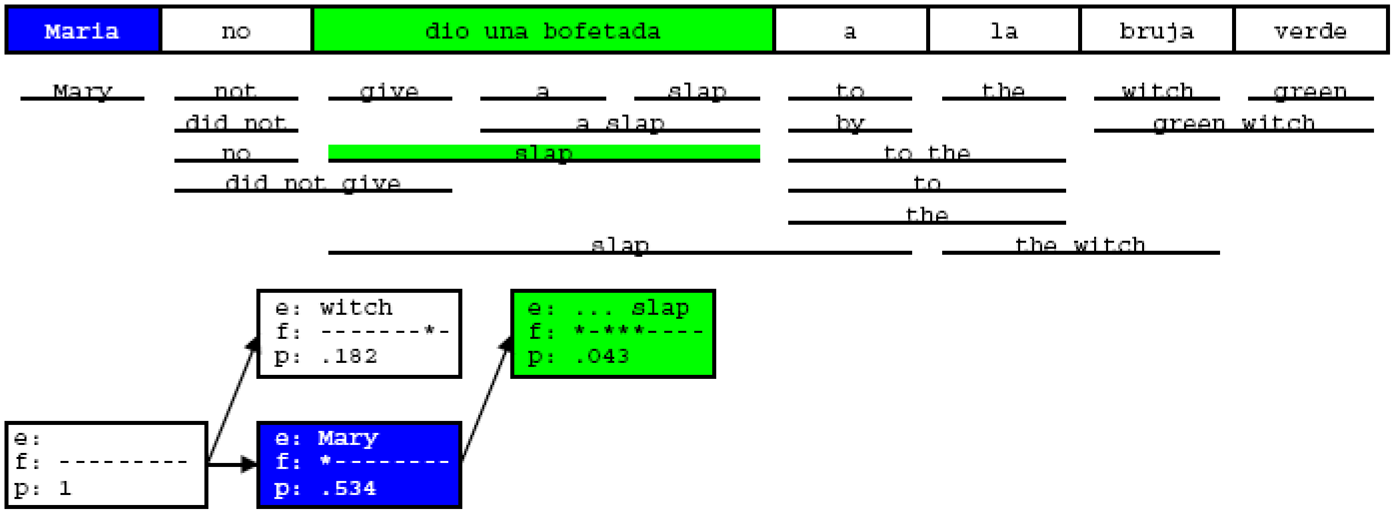
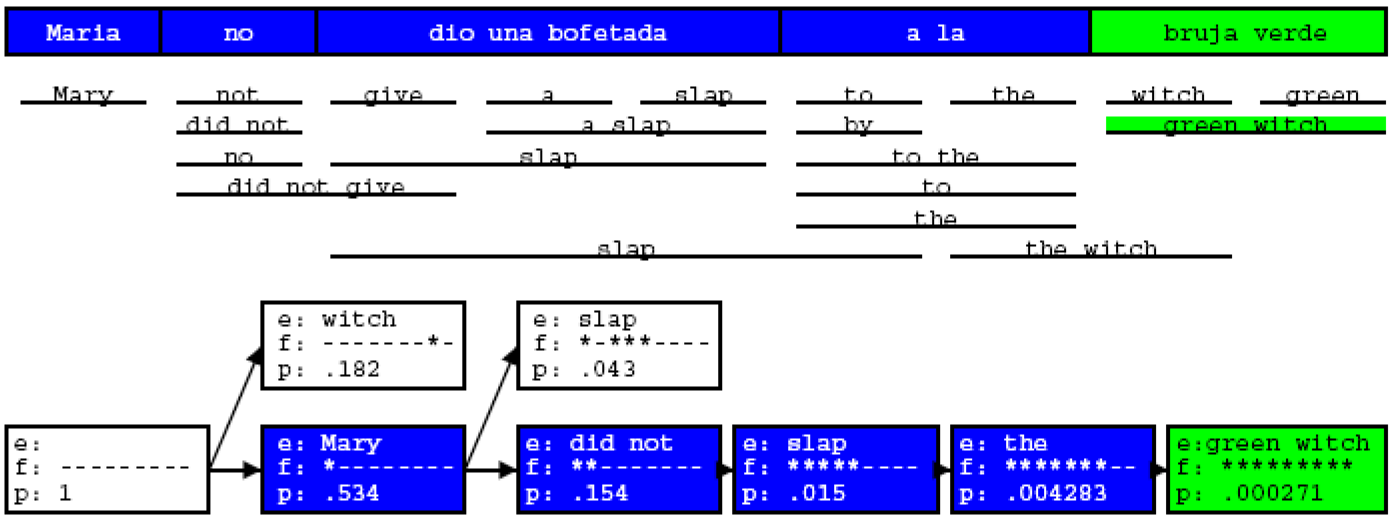
Hypothesis Expansion



- Further *hypothesis expansion*

Hypothesis Expansion



- ... until all foreign words *covered*
  - find *best hypothesis* that covers all foreign words
  - *backtrack* to read off translation

Slide from Koehn 2008

Outline

- *Recap*
- Optimizing parameters
- Deriving the log-linear model
- Tuning the log-linear model
- Adding new features

Introduction

- We have seen that using Bayes' Rule we can decompose the problem of maximizing P(e|f)

$$\underset{e}{\operatorname{argmax}}\ P(e \mid f) = \underset{e}{\operatorname{argmax}}\ P(f \mid e)\ P(e)$$

Basic phrase-based model

- We make the Viterbi assumption for alignment (not summing over alignments, just taking the best one)
- We know how to implement P(f,a|e) using a phrase-based translation model composed of a phrase-generation model and a reordering model
- We know how to implement P(e) using a trigram model and a length bonus

$$P_{TM}(f,a \mid e)\ \ P_{D}(a)\ \ P_{LM}(e)\ \ C^{\mathrm{length}(e)}$$

Example

Source: |Morgen| |fliege| |ich| |nach Kanada|

Hyp 1: |Tomorrow| |I| |will fly| |to Canada|

Hyp 2: |Tomorrow| |fly| |I| |to Canada|

- What do we expect the numbers to look like?

	Phrase Trans	Reordering	Trigram LM	Length bonus
Hyp 1	Good	$Z^4 < 1$	Good	C^6
Hyp 2	Good	$Z^0 = 1$	Bad	$C^5 < C^6$

What determines which hyp is better?

- Which hyp gets picked?
  - Length bonus and trigram like hyp 1
  - Reordering likes hyp 2
- If we optimize Z and C for best performance, we will pick hyp 1

	Phrase Trans	Reordering	Trigram LM	Length bonus
Hyp 1	Good	$Z^4 < 1$	Good	C^6
Hyp 2	Good	$Z^0 = 1$	Bad	$C^5 < C^6$

How to optimize Z and C?

- Take a new corpus “dev” (1000 sentences, with gold standard references so we can score BLEU)
- Try out different parameters. [Take last C and Z printed]. How many runs?

```
Best = 0;
For (Z = 0; Z <= 1.0; Z += 0.1)
  For (C = 1.0; C <= 3.0; C += 0.1)
      Hyp = run decoder(C,Z,dev)
      If (BLEU(Hyp) > Best)
         Best = BLEU(Hyp)
         Print C and Z
```

Adding weights

- But what if we know that the language model is really good; or really bad?
- We can take the probability output by this model to an exponent

$$P_{LM}(e)^{\lambda_{LM}}$$

- If we set the exponent to a very large positive number then we trust $P_{LM}(e)$ very much
  - If we set the exponent to zero, we do not trust it at all (probability is always 1, no matter what **e** is)

- Add a weight for each component

  (Note, omitting length bonus here, it will be back soon; we'll set C to 1 for now so it is gone)

$$P_{TM}(f, a \mid e)^{\lambda_{TM}} \; P_D(a)^{\lambda_D} \; P_{LM}(e)^{\lambda_{LM}}$$

- To get a conditional probability, we will divide by all possible strings e and all possible alignments a

$$P(e, a \mid f) = \frac{P_{TM}(f, a \mid e)^{\lambda_{TM}} \; P_D(a)^{\lambda_D} \; P_{LM}(e)^{\lambda_{LM}}}{\sum_{e',a'} P_{TM}(f, a' \mid e')^{\lambda_{TM}} \; P_D(a')^{\lambda_D} \; P_{LM}(e')^{\lambda_{LM}}}$$

- To solve the decoding problem we maximize over e and a. But the term in the denominator is constant!

$$\operatorname{argmax}_{e,a} P(e,a \mid f) = \operatorname{argmax}_{e,a} \frac{P_{TM}(f,a \mid e)^{\lambda_{TM}}\ P_D(a)^{\lambda_D}\ P_{LM}(e)^{\lambda_{LM}}}{\sum_{e',a'} P_{TM}(f,a' \mid e')^{\lambda_{TM}}\ P_D(a')^{\lambda_D}\ P_{LM}(e')^{\lambda_{LM}}}$$

$$= \operatorname{argmax}_{e,a}\ P_{TM}(f,a \mid e)^{\lambda_{TM}}\ P_D(a)^{\lambda_D}\ P_{LM}(e)^{\lambda_{LM}}$$

- Now let's add C back in and take the log (see formulation in a couple of slides)
- We now have two problems
  - Optimize Z and C and the three lambdas
  - Exponentiation is slow
    - Let’s solve this one first…

Log probabilities

- Convenient to work in log space
- Use log base 10 because it is easy for humans
- log(1)=0 because $10^0 = 1$
- log(1/10)=-1 because $10^{-1} = 1/10$
- log(1/100)=-2 because $10^{-2} = 1/100$
- Log(a*b) = log(a)+log(b)
- Log(a^b) = b log(a)

So let's maximize the log

$$\operatorname{argmax}_{e,a} P(e, a \mid f)$$

$$= \operatorname{argmax}_{e,a} P_{TM}(f, a \mid e)^{\lambda_{TM}} P_D(a)^{\lambda_D} P_{LM}(e)^{\lambda_{LM}} C^{\mathrm{length}(e)}$$

So let's maximize the log

$$\text{argmax}_{e,a} P(e, a \mid f)$$

$$= \text{argmax}_{e,a} \; P_{TM}(f, a \mid e)^{\lambda_{TM}} \; P_D(a)^{\lambda_D} \; P_{LM}(e)^{\lambda_{LM}} \, C^{\text{length(e)}}$$

$$= \text{argmax}_{e,a} \log\left(P_{TM}(f, a \mid e)^{\lambda_{TM}} \; P_D(a)^{\lambda_D} \; P_{LM}(e)^{\lambda_{LM}} \, C^{\text{length(e)}}\right)$$

So let's maximize the log

$$\mathrm{argmax}_{e,a} P(e,a \mid f)$$

$$= \mathrm{argmax}_{e,a}\ P_{TM}(f,a \mid e)^{\lambda_{TM}}\ P_D(a)^{\lambda_D}\ P_{LM}(e)^{\lambda_{LM}}\ C^{\mathrm{length}(e)}$$

$$= \mathrm{argmax}_{e,a} \log(P_{TM}(f,a \mid e)^{\lambda_{TM}}\ P_D(a)^{\lambda_D}\ P_{LM}(e)^{\lambda_{LM}}\ C^{\mathrm{length}(e)})$$

$$= \mathrm{argmax}_{e,a} \log(P_{TM}(f,a \mid e)^{\lambda_{TM}}) + \log(P_D(a)^{\lambda_D})$$

$$+ \log(\ P_{LM}(e)^{\lambda_{LM}}) + \log(\ C^{\mathrm{length}(e)}))$$

So let's maximize the log

$$\text{argmax}_{e,a} P(e, a \mid f)$$

$$= \text{argmax}_{e,a} \; P_{TM}(f, a \mid e)^{\lambda_{TM}} \; P_D(a)^{\lambda_D} \; P_{LM}(e)^{\lambda_{LM}} \, C^{\text{length(e)}}$$

$$= \text{argmax}_{e,a} \log(P_{TM}(f, a \mid e)^{\lambda_{TM}} \; P_D(a)^{\lambda_D} \; P_{LM}(e)^{\lambda_{LM}} \, C^{\text{length(e)}})$$

$$= \text{argmax}_{e,a} \log(P_{TM}(f, a \mid e)^{\lambda_{TM}}) + \log(P_D(a)^{\lambda_D})$$
$$+ \log(\; P_{LM}(e)^{\lambda_{LM}}) + \log(\; C^{\text{length(e)}}))$$

$$= \text{argmax}_{e,a} \lambda_{TM} \log(P_{TM}(f, a \mid e)) + \lambda_D \log(P_D(a))$$
$$+ \lambda_{LM} \log(\; P_{LM}(e)) + \log(\; C^{\text{length(e)}}))$$

Let's change the length bonus

$$= \text{argmax}_{\text{e,a}}\ \lambda_{TM} \log(\text{P}_{\text{TM}}(\text{f,a} \mid \text{e})) + \lambda_D \log(\text{P}_{\text{D}}(\text{a}))$$
$$+ \lambda_{LM} \log(\text{P}_{\text{LM}}(\text{e})) + \lambda_{LB} \log(10^{\text{length(e)}})$$

$$= \text{argmax}_{\text{e,a}}\ \lambda_{TM} \log(\text{P}_{\text{TM}}(\text{f,a} \mid \text{e})) + \lambda_D \log(\text{P}_{\text{D}}(\text{a}))$$
$$+ \lambda_{LM} \log(\text{P}_{\text{LM}}(\text{e})) + \lambda_{LB} \text{length(e)}$$

We set C=10 and add a new lambda, then simplify

Length penalty

$$= \text{argmax}_{e,a} \ \lambda_{TM} \log(P_{TM}(f, a \mid e)) + \lambda_D \log(P_D(a)) + \lambda_{LM} \log(P_{LM}(e)) + \lambda_{LP}(-\text{length}(e))$$

We like the values we work with to be zero or less (like log probabilities)

We change from a length bonus to a length penalty (LP)

But we know we want to encourage longer strings so we expect that this lambda will be negative!

Reordering

$$= \mathrm{argmax}_{\,e,a}\ \lambda_{TM}\log(\mathrm{P}_{\mathrm{TM}}(\mathrm{f},\mathrm{a}\,|\,\mathrm{e})) + \lambda_{D}(\text{-D(a)})$$
$$+ \lambda_{LM}\log(\mathrm{P}_{\mathrm{LM}}(\mathrm{e})) + \lambda_{LP}(\text{-length(e)})$$

Do the same thing for reordering. As we do more jumps, “probability” should go down.

So use –D(a)

D(a) is the sum of the jump distances (4 for hyp 1 in our previous example)

Log-linear model

- So we now have a log-linear model with four components, and four lambda weights
  - The components are called feature functions
    - Given **f**, **e** and/or **a** they generate a log probability value
    - Or a value looking like a log probability (Reordering, Length Penalty)
  - Other names: features, sub-models
- This is a discriminative model, not a generative model

The birth of SMT: 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)

Slide from Koehn 2008

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 the 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

Slide from Koehn 2008

Search for the log-linear model

- We've derived the log-linear model
  - We can use our beam decoder to search for the English string (and alignment) of maximum probability
    - We only change it to **sum** (lambdas times log probabilities)
    - Rather than multiplying unweighted probabilities as it did before

$$= \operatorname{argmax}_{\mathrm{e,a}} \; \lambda_{TM} \log(\mathrm{P_{TM}}(\mathrm{f} \mid \mathrm{e})) + \lambda_{D}(\text{-D(a)}) + \lambda_{LM} \log(\mathrm{P_{LM}}(\mathrm{e})) + \lambda_{LP}(\text{-length(e)})$$

Discriminative training problem: optimizing lambda

- We are looking for the best lambda vector
  - A lambda vector consists of lambda scalars (4 for our model right now)
- How do we get an optimal lambda vector?
- We can use nested for-loops as we did before for C and Z
  - We need to try out a lot of values for the lambda scalars though, the differences could be very subtle
  - Many, many decoder runs; these take 10 minutes or longer each!
- At least we can reduce number of decoder runs
  - Use n-best lists

Discriminative training

- Training set (*development set*)
  - different from original training set
  - small (maybe 1000 sentences)
  - must be different from test set

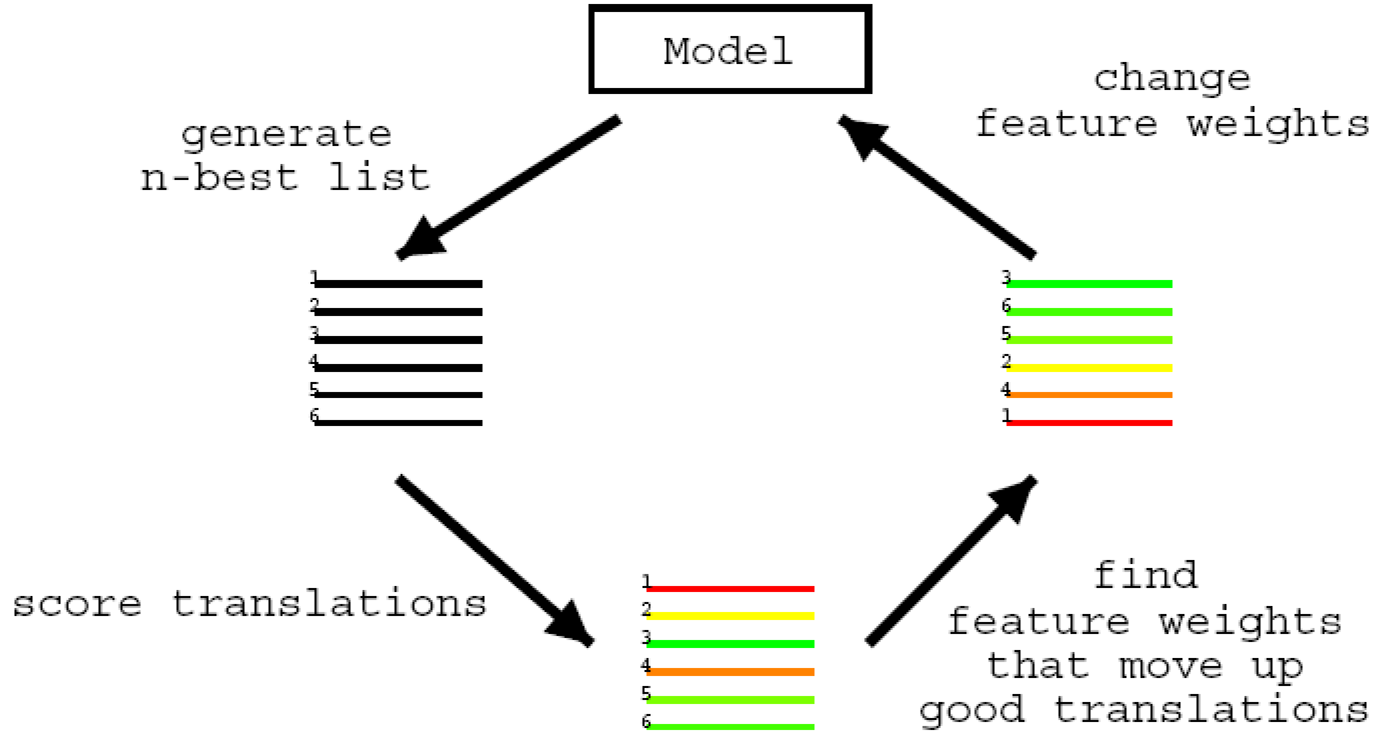
- Current model *translates* this development set
  - *n-best list* of translations (n=100, 10000)
  - translations in n-best list can be *scored*

- Feature weights are *adjusted*

- N-Best list generation and feature weight adjustment repeated for a number of iterations

Slide from Koehn 2008

Learn feature weights



Slide from Koehn 2008

Learning Task

Source: |Morgen| |fliege| |ich| |nach Kanada|

Hyp 1: |Tomorrow| |I| |will fly| |to Canada|

Hyp 2: |Tomorrow| |fly| |I| |to Canada|

Assume that Hyp 1 has a better BLEU score

	Phrase Trans	Reordering	Trigram LM	Length
Hyp 1	-1	-4	-3	-6
Hyp 2	-1	0	-5	-5

Learning Task

Suppose we start with an initial lambda vector: 1 1 1 -1

Then: hyp 1 has a log score of -2 (1/100 probability)

hyp 2 has a log score of -1 (1/10 probability)

This is poor! Hyp 2 will be selected

	Phrase Trans	Reordering	Trigram LM	Length
Hyp 1	-1	-4	-3	-6
Hyp 2	-1	0	-5	-5

Learning Task

We would like to find a vector like: 1 0.5 2 -1

hyp 1 has a log score of -3

hyp 2 has a log score of -6

Hyp 1 is correctly selected!

	Phrase Trans	Reordering	Trigram LM	Length
Hyp 1	-1	-4	-3	-6
Hyp 2	-1	0	-5	-5

Learning Task

N-best lists contain several sentences and hypotheses for each sentence

The lambda vector 1 0.5 2 -1 picks Hyp 1 in the first sentence, and Hyp 2 in the second sentence.

Suppose sentence 2 Hyp 1 is better. Then choose a lambda like: 3 0.5 2 -1

It is easy to see that this does not change the ranking of the hypotheses in sentence 1.

Sentence	Hypothesis	Phrase Trans	Reordering	Trigram LM	Length bonus
1	Hyp 1	-1	-4	-3	-6
1	Hyp 2	-1	0	-5	-5
2	Hyp 1	-2	0	-3	-3
2	Hyp 2	-3	0	-2	-3

N-best lists result in big savings

- Run the for-loops on a small collection of hypotheses, do decoder runs only when you have good settings

```
Initialize: start with empty hypothesis collection
LOOP:
   – Run the decoder with current lambda vector and add n-
     best list hypotheses to our collection
   – Score collection of hypotheses with BLEU
   – Use nested-for-loop to change individual lambda
     scalars in vector to get better BLEU on collection
   – End program if lambda vector did not change
```

- OK, so we know how to set the lambda vector for our four feature functions
  - This means depending on the task we might, for instance, penalize reordering more or less
  - This is determined automatically by the performance on the dev corpus
- But what about new features?

New Feature Functions

- We can add new feature functions!
  - Simply add a new term and an associated lambda
- Can be anything that can be scored on a partial hypothesis
  - (remember how the decoder works!)
  - Can be function of **e**, **f** and/or **a**
  - Can be either log probability (e.g., Trigram), or just look like one (e.g., Length Penalty)
- These can be very complex features to very simple features
  - Length penalty is simple
  - Phrase translation is complex
  - With right lambda settings they will trade-off against each other well!

New Feature Functions

- Features can overlap with one another!
  - In a generative model we do a sequence of steps, no overlapping allowed
  - In Model 1, you can't pick a generated word using two probability distributions
    - Note: Interpolation is not an answer here, would add the optimization of the interpolation weight into EM
    - Better to rework generative story if you must (this is difficult)
  - With a log-linear model we can score the probability of a phrase block using many different feature functions, because the model is not generative

Knowledge sources

- Many different **knowledge sources** useful
  - language model
  - reordering (distortion) model
  - phrase translation model
  - word translation model
  - word count
  - phrase count
  - drop word feature
  - phrase pair frequency
  - additional language models
  - additional features

Slide from Koehn 2008

Revisiting discriminative training: methods to adjust feature weights

- We will wind up with a lot of lambda scalars to optimize
- But there are algorithms to deal with this that are more efficient than nested for-loops
- In all cases, we have the same log-linear model
  - The only difference is in how to optimize the lambdas
  - We saw one way to do this already
    - Using nested for-loops on n-best lists
  - We will keep using n-best lists (but not nested for-loops)

Minimum Error Rate Training

- Maximize quality of top-ranked translation
  - Similarity according to metric (BLEU)
  - Implemented in Moses toolkit

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
```

Slide from Koehn 2008

MERT is like “un-nesting” the for-loops

```
StartLambda = 1 1 1 -1
LOOP:
BestBLEU[1..4] = 0
For (i = 1 to 4)
  TryLambda = StartLambda
   For (L = 1.0; L <= 3.0; L += 0.1)
        TryLambda[i] = L
         Hyp = best_hyps_from_nbest_list(TryLambda)
         If (BLEU(Hyp) > BestBLEU[i])
            BestBLEU[i] = BLEU(Hyp)
            BestLambda[i] = L
```

Then simply check BestBLEU[1..4] for the best score.

Suppose it is BestBLEU[2].

Set StartLambda[2] = BestLambda[2] and go to top of loop (until you get no improvement).

However MERT is better than that

- We will not check discrete values (1.0, 1.1, ..., 3.0)
- We will instead do an exact line minimization in one pass through the n-best list
- Key observation is that varying just one weight means:
  - The score of each hypothesis (as we vary the weight) can be viewed as a line
  - For each sentence, we can look at the intercept points of these lines to see where the hypothesis with the best model score changes

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

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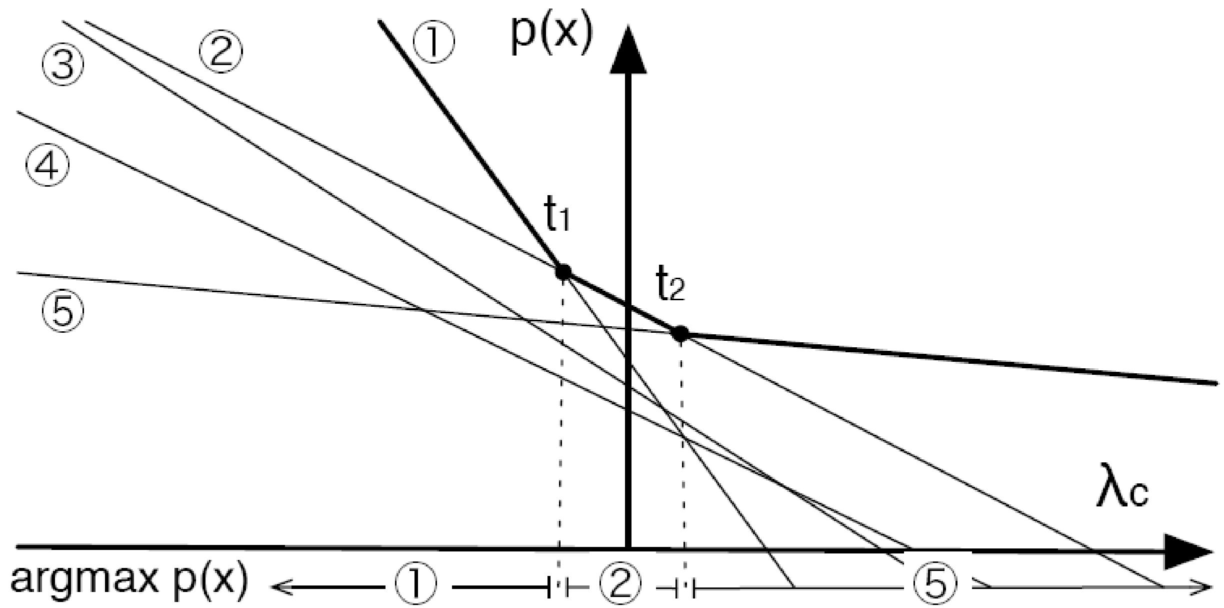
Translations for one Sentence



- each translation is a line $p(\mathbf{e}_i|\mathbf{f}) = \lambda a_i + b_i$
- the model-best translation for a given λ (x-axis), is highest line at that point
- there are one a few *threshold points* t_j where the model-best line changes

Slide from Koehn 2008

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

Slide from Koehn 2008

Minimum Error Rate Training [Och, ACL 2003]

- Maximize quality of top-ranked translation
  - Similarity according to metric (BLEU)
- This approach only works with up to around 20 feature functions
  - But very fast and easy to implement
- Implementation comes with Moses

Maximum Entropy [Och and Ney, ACL 2002]

- Match expectation of feature values of model and reference translation
- Log-linear models are also sometimes called Maximum Entropy models (when trained this way)
- Great for binary classification, very many lightweight features
  - Also is a convex optimization – no problems with local maxima in the optimization
- Doesn‘t work well for SMT

Ordinal Regression [Chiang et al., NAACL 2009; many others previously]

- Separate k worst from the k best translations
  - E.g., separate hypotheses with lowest BLEU from hypotheses with highest BLEU
  - Approximately maximizes the **margin**
    - Support Vector machines do this non-approximately (but are too slow)
  - Often done in an online fashion, one sentence at a time (i.e., original Chiang approach)
- Recently become very popular
- Moses comes with Batch MIRA (not online), we use this
- Related approach (also in Moses) is Pairwise Ranking Optimization
- Both approaches scale to thousands of feature functions

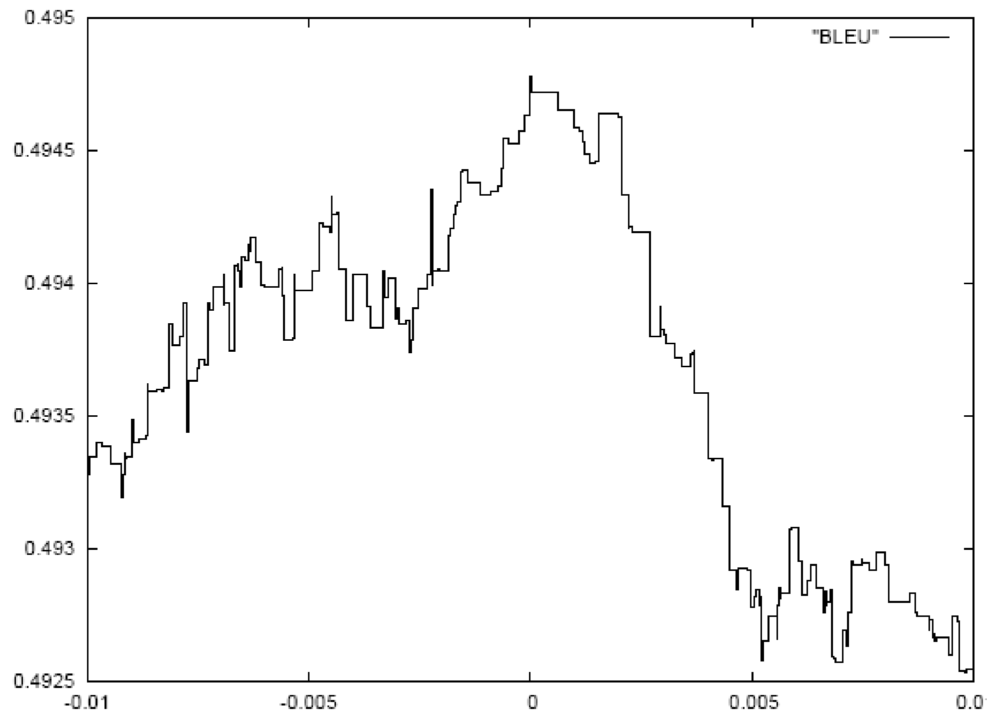
Conclusion

- We have defined log-linear models
- And shown how to automatically tune them
- Log-linear models allow us to use any feature function that our decoder can score
  - Must be able to score a partial hypothesis extended from left to right (decoding/search lecture)
- Log-linear models are now used almost everywhere (also in non-structured prediction)

- Thanks for your attention!

BLEU error surface

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



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