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Applied Language Technology
Tuning

Today's Class

- Parameter Tuning
  - Minimum Error Rate Training (MERT)

Parameter Optimization

- Statistical MT systems have a number of models
  - Translation model: $p(f|e)$ and $p(e|f)$
  - Language model: $p(e)$
  - Linear distortion
  - ...
- How important is each model?
  - Weight (parameterize) each model, e.g., $p(f|e)^{\lambda_1} \dots p(e)^{\lambda_3} \dots$
  - Question: how important is, e.g., the language model wrt the other models?
- Parameter optimization (or tuning) aims to find the weights that result in the best performance wrt a objective evaluation metric, e.g. BLEU

Parameter Optimization

src: er geht ja nicht nach Hause

ref: he does not go home

$\lambda_1 = 0.1$ and $\lambda_2 = 0.2$

translation	feature values		score	BLEU
it is not under house	-2.0	-2.0	$\mathbf{-0.600}$	0.20
he is not to go home	-0.5	-3.0	-0.650	0.33
he does not home	-4.0	-1.5	-0.700	$\mathbf{1.00}$
it is not packing	-3.0	-3.0	-0.900	0.00
he is not for home	-5.0	-6.0	-1.700	0.20

Parameter Optimization

src: er geht ja nicht nach Hause

ref: he does not go home

$\lambda_1 = 0.05$ and $\lambda_2 = 0.3$

translation	feature values		score	BLEU
it is not under house	-2.0	-2.0	-0.700	0.20
he is not to go home	-0.5	-3.0	-0.925	0.33
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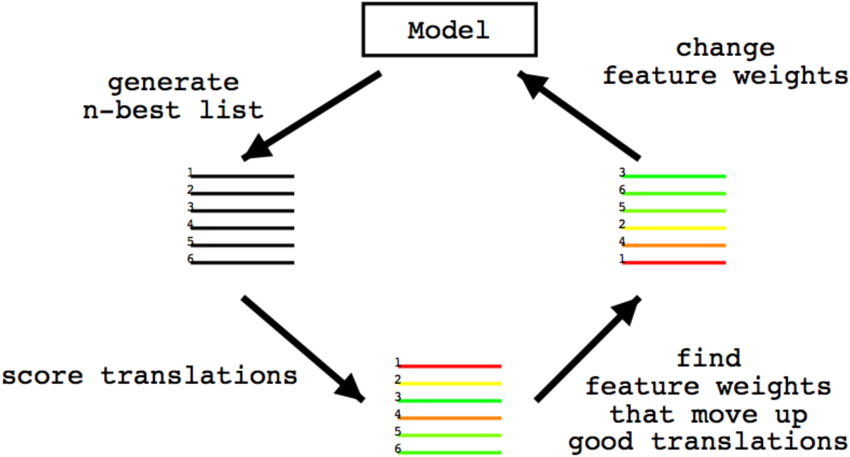
it is not packing	-3.0	-3.0	-1.050	0.00
he is not for home	-5.0	-6.0	-2.050	0.20

Parameter Estimation

- Data:
  - **Training data:** bitext to learn the translation model (and maybe a lexicalized distortion model); 50K+ sentence pairs
  - **Development data:** data that is not part of the bitext but is used to optimize the parameters iteratively; 1-2K sentence pairs
  - **Test data:** unseen data that is used to compare different methods; 1-2K sentence pairs
- Just like for the bitext, there must be known translations for the development and test data (and preferably multiple translations)

Parameter Estimation Cycle



Optimizing for BLEU

- In general: always optimize towards the objective metric that is used for final evaluation
- BLEU is
  - most commonly used evaluation metric
  - fast and easy to calculate
  - correlates reasonably well with human judgments
- BLEU is not
  - very stable on the sentence level, but on the corpus level
  - differentiable

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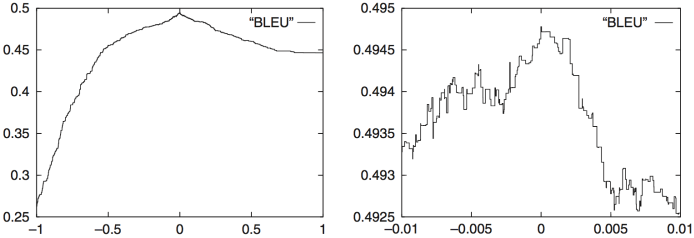


Minimum Error Rate Training (MERT)

- Given a set of n-best lists, how to find best weights?
  - Non-convex, non-differentiable objective
  - Too many features to use grid search
- Minimum Error Rate Training (MERT)
  - MT optimization algorithm by Och (2003)
  - Line search - one direction (weight) at a time
  - Keep going until no improvement possible
  - Uses random restarts

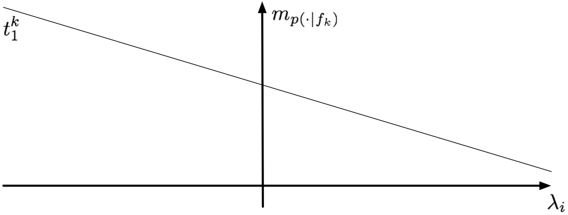
Powell Search

- Explore high-dimensional parameter space
- Select one parameter (line) at a time and find optimal value
- If the score of the objective metric at this point increases, then select parameter value and continue with remaining parameters
- Analogy: Find the location with the highest altitude in a city (e.g., San Francisco) by walking through the street grid
  - Walk down one street until the highest point has been reached
  - At this crossing, take the street along the other dimension

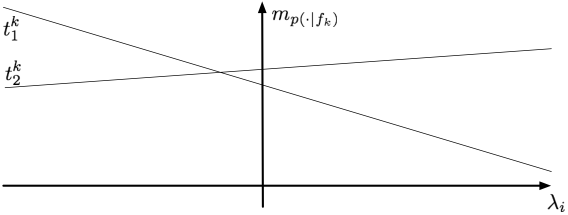
MERT Line Search

- The model score for a translation candidate e of source sentence f is defined as: $\text{score}(e|f) = \sum_{m=1}^{M} \lambda_m h_m(e,f)$
- If we focus on one parameter at a time, e.g. λ_i
- We can rewrite this as:
  $\text{score}(e|f) = h_i(e,f)\lambda_i + \sum_{m \neq i} \lambda_m h_m(e,f)$
- Which is of the form: $a\lambda_i + b$
  - which is a line
  - where a is the slope and b is the y-intercept
- We vary one parameter at a time, the others remain fixed
- Varying this parameter affects the overall score of every hypothesis
- Find the parameter that promotes the hypothesis optimizing the objective function (BLEU)

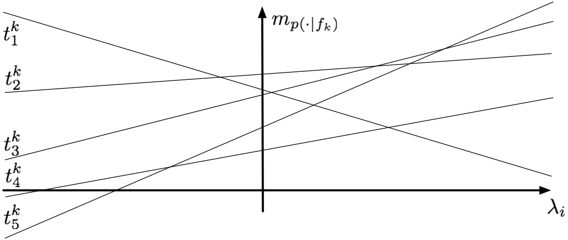
MERT Line Search



MERT Line Search



MERT Line Search



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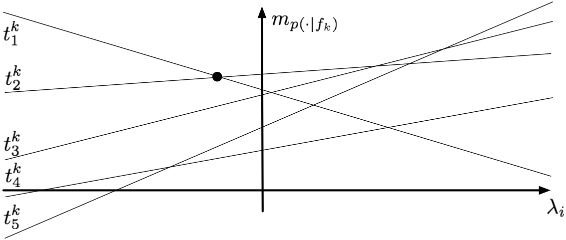

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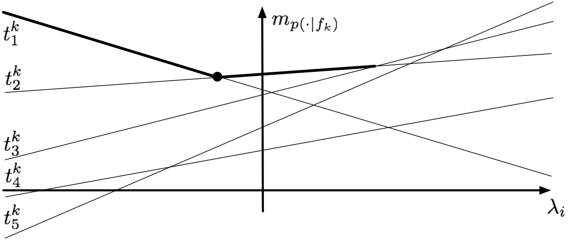

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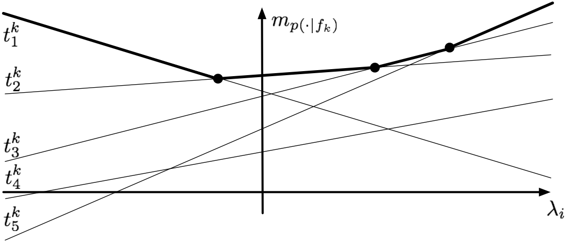

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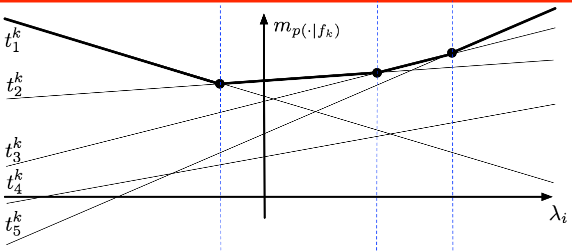

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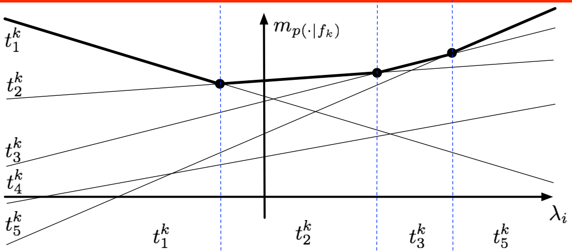
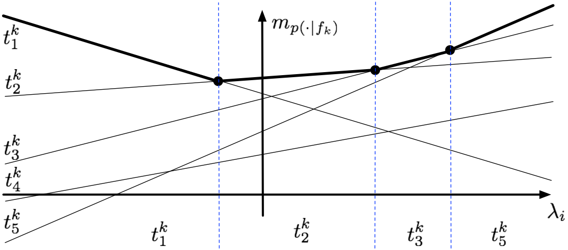


Finding Intersection Points

- Find the line with the steepest descent (i.e. smallest slope): l
- For each other line l', compute the intersection by solving for λ_i in $a\lambda_i + b = a' + \lambda_i + b'$
- The line l' with the closest intersection point becomes the current line
  - Again, find the line with the closest intersection point
  - ...
- For each interval of intersection points, we store the corresponding translation candidate

Aggregating Intervals



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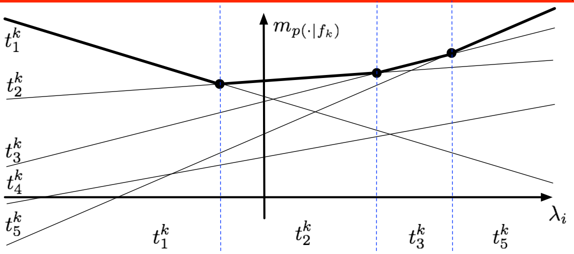

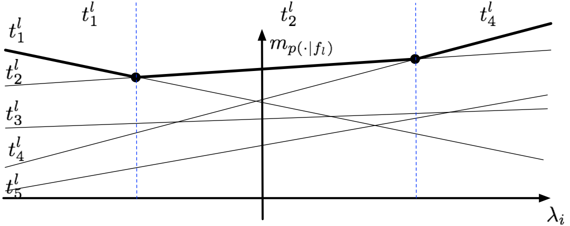

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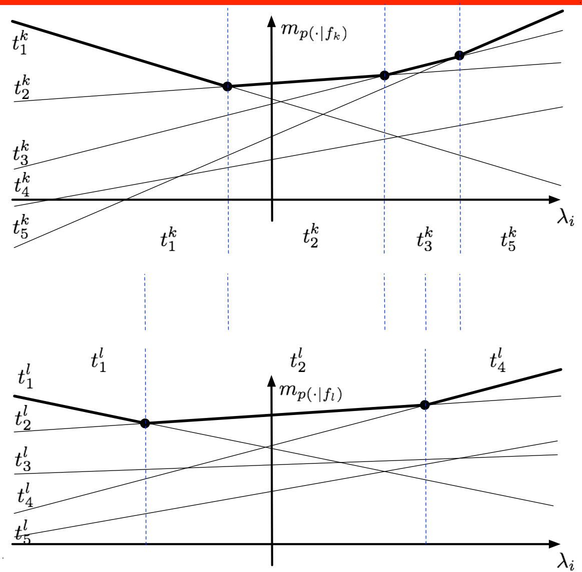

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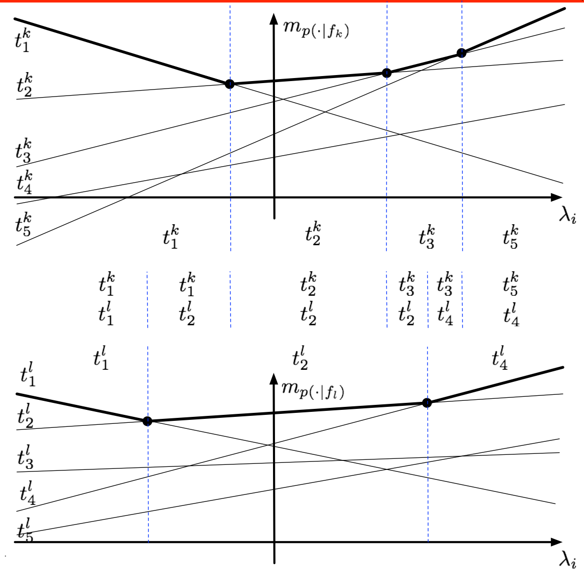


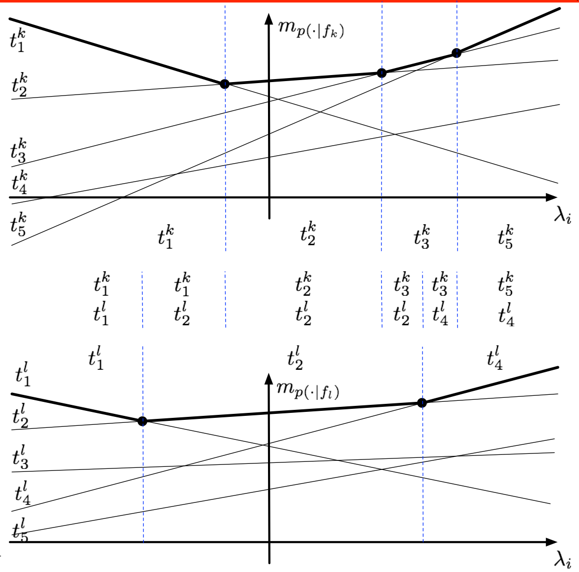
Computing BLEU

- BLEU can be computed based on the component scores only:
- Given a translation t^f for a foreign sentence f with reference translations R_f we can $\text{bleu\_vec}(t^f, R_f)$
- $\text{bleu\_vec}(t^f, R_f) = (c_1, n_1, c_2, n_2, c_3, n_3, c_4, n_4, l)$
  - where c_i is the number of correct n-grams of length i
  - where n_i is the number of total n-grams of length i
  - l is the length of the reference translation
- Corpus BLEU can now be computed as: $\text{BLEU}(\sum_{f \in F} \text{bleu\_vec}(t_1^f, R_f))$
  - where t_1^f is the 1-best translation of f

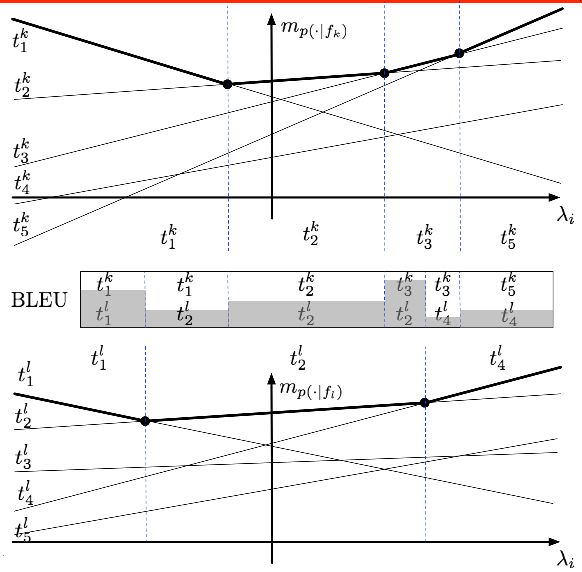
Computing BLEU

- Let $\text{all\_vec} = \sum_{f \in F} \text{bleu\_vec}(t_1^f, R_f)$
- How does the overall BLEU score change if we use translations t_2^k and t_2^l instead of t_1^k and t_1^l?
  $$\text{all\_vec} - (\text{bleu\_vec}(t_1^k, R_k) + \text{bleu\_vec}(t_1^l, R_l)) \\ + \text{bleu\_vec}(t_2^k, R_k) + \text{bleu\_vec}(t_2^l, R_l)$$
- We can now efficiently compute BLEU scores for all intersection point intervals

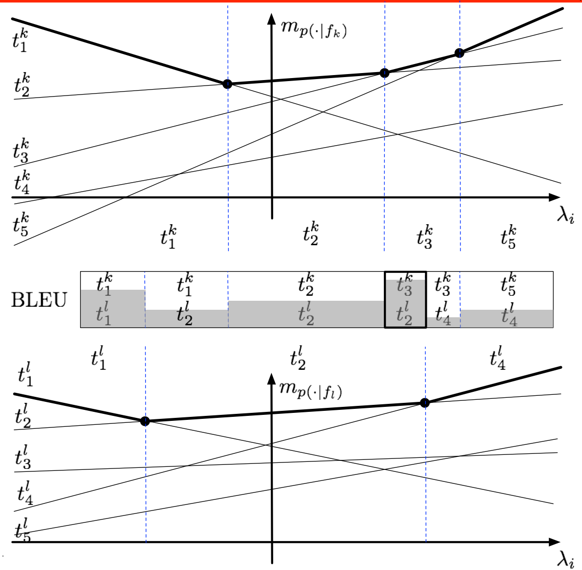
Interval BLEU Scores



Interval BLEU Scores



Interval BLEU Scores



MERT Iteration

- The optimal parameter value for λ_i falls into the interval $[m,n]$ with the highest BLEU scores
- If the BLEU score for interval $[m,n]$ is higher than the BLEU score using the parameters of the previous iteration (t) we set $\lambda_i^{(t+1)} = \frac{n-m}{2}$, else $\lambda_i^{(t+1)} = \lambda_i^{(t)}$
- Next we continue optimizing one of the remaining parameters using $(\lambda_1^{(t)}, \ldots, \lambda_i^{(t+1)}, \ldots, \lambda_M^{(t)})$
- Continue until all parameters have been updated for iteration $t+1$
- Decode with new parameters of iteration $t+1$
  - Optimize again each parameter at a time
  - Repeat until no further BLEU score improvements

MERT N-Best Lists

- During parameter optimization we consider the n-best translations of a source sentence at each iteration
- Ideally, we want to compare *all* possible translation candidates
  - Use large values of n for n-best list $\rightarrow$ limited variation with n-best list
  - Use lattices instead of n-best lists
- Accumulate n-best lists from all previous iterations
  - n-best list of sentence f in iteration t is the union of all n-best lists for f from iterations $0, \ldots t$
  - Remove entries with identical derivations
  - Or, better, remove entries with identical feature values

MERT Random Restarts

- By iteratively optimizing the parameters we generate a sequence of the form

$$
\begin{array}{c}
(\lambda_1^{(0)}, \ldots, \lambda_i^{(0)}, \ldots, \lambda_M^{(0)}) \\
\vdots \\
(\lambda_1^{(t)}, \ldots, \lambda_i^{(t)}, \ldots, \lambda_M^{(t)}) \\
\downarrow \\
(\lambda_1^{(t+1)}, \ldots, \lambda_i^{(t+1)}, \ldots, \lambda_M^{(t+1)}) \\
\vdots
\end{array}
$$

- Susceptible to local optima as each iteration only depends on previous values
- Include random starting points
  - Optimize using the best parameters wrt previous iteration
  - Optimize using r random parameter values (r typically 19)

MERT Review

- MERT is
  - (still) the most widely used parameter optimization within SMT
  - adaptable to a number of different MT metrics (BLEU, WER, TER, ...) → Z-MERT (Zaidan, 2009)
  - easily parallelizable: 1 thread per (random) restart
  - good in achieving convergence in reasonable time
- MERT is not
  - good in scaling up to larger numbers of parameters (limit at around 20-30 features)
  - very robust, partly due to random restarts and initialization
  - susceptible to local optima when finding maximum BLEU scores for the intersection intervals

Recap

- Parameter Tuning
- Minimum Error Rate Training (MERT)
  - MERT line search
  - Finding intersection points
  - Aggregating of BLEU scores for intervals
  - N-best list accumulation
  - MERT random restarts