Hill Climbing on Speech Lattices: A New Rescoring Framework

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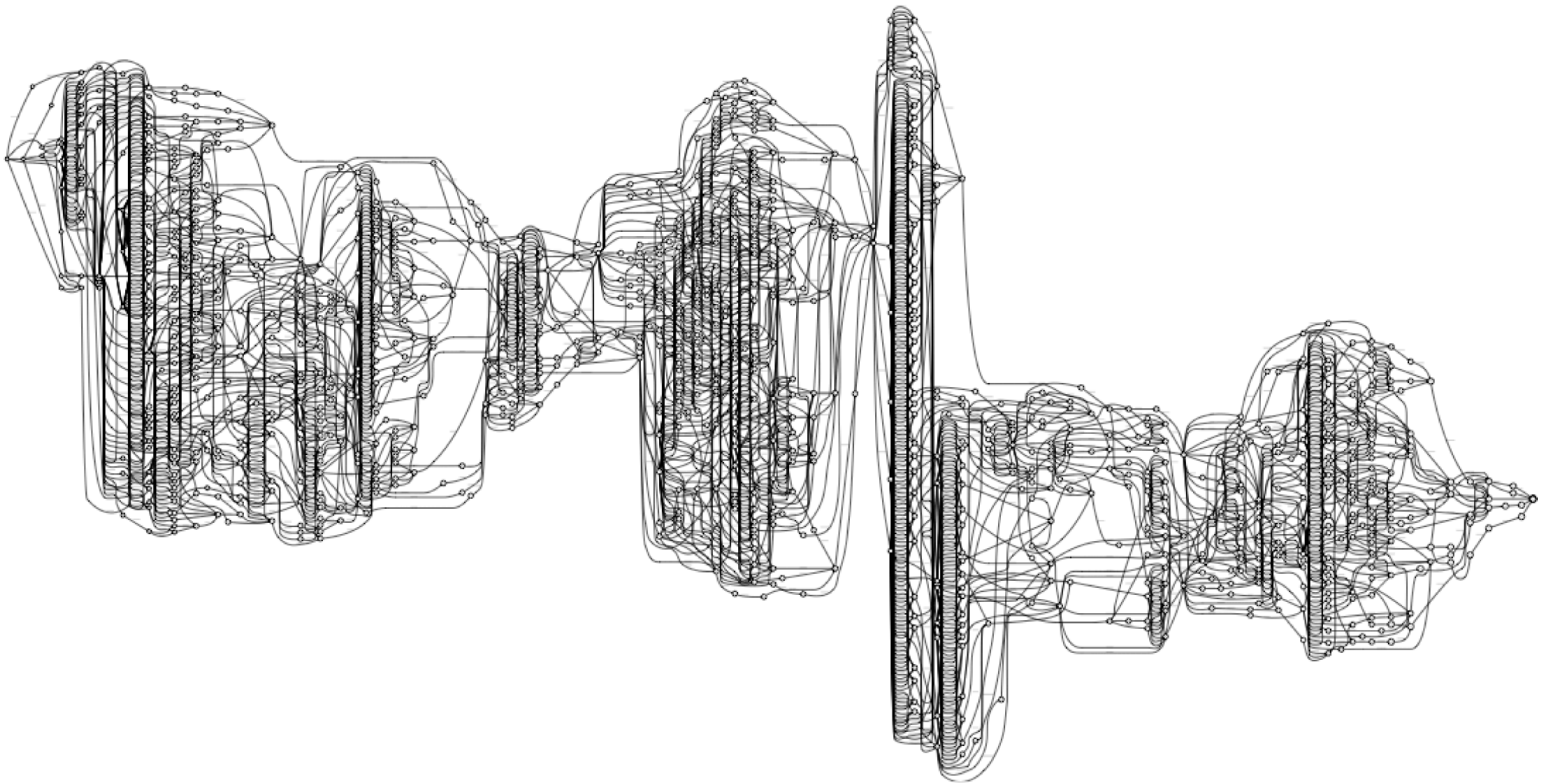
Motivation

- Availability of large amounts of training data and computational resources
  - building more complex models with sentence level knowledge and longer dependencies is the active area of research for ASR
- Many of these complex and sophisticated models *can not* be integrated into the **first pass decoding**
- They *can not* be represented as **weighted finite-state automata** (WFSA)
  - difficult to even incorporate them in a **lattice-rescoring** pass

Motivation



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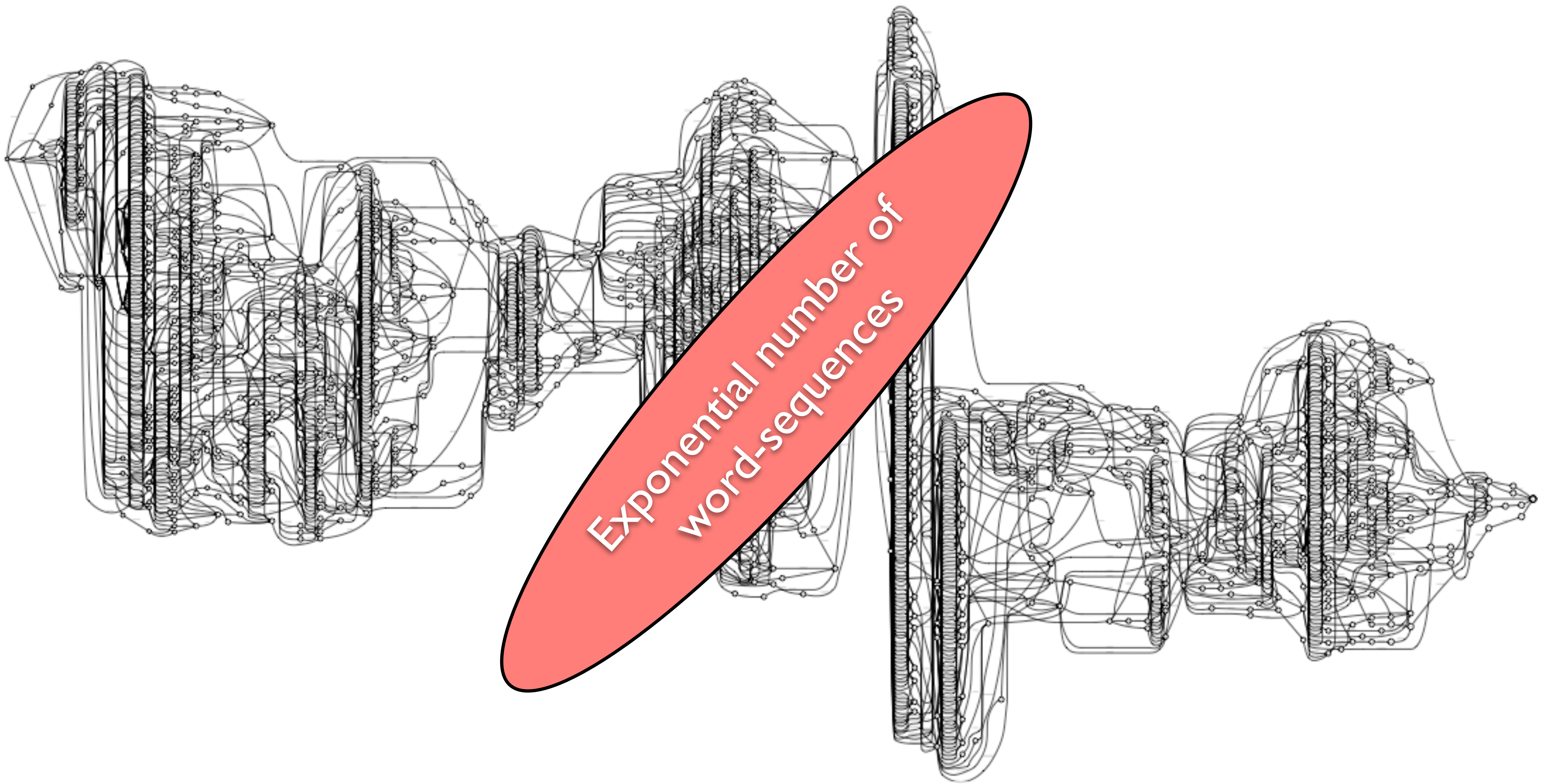

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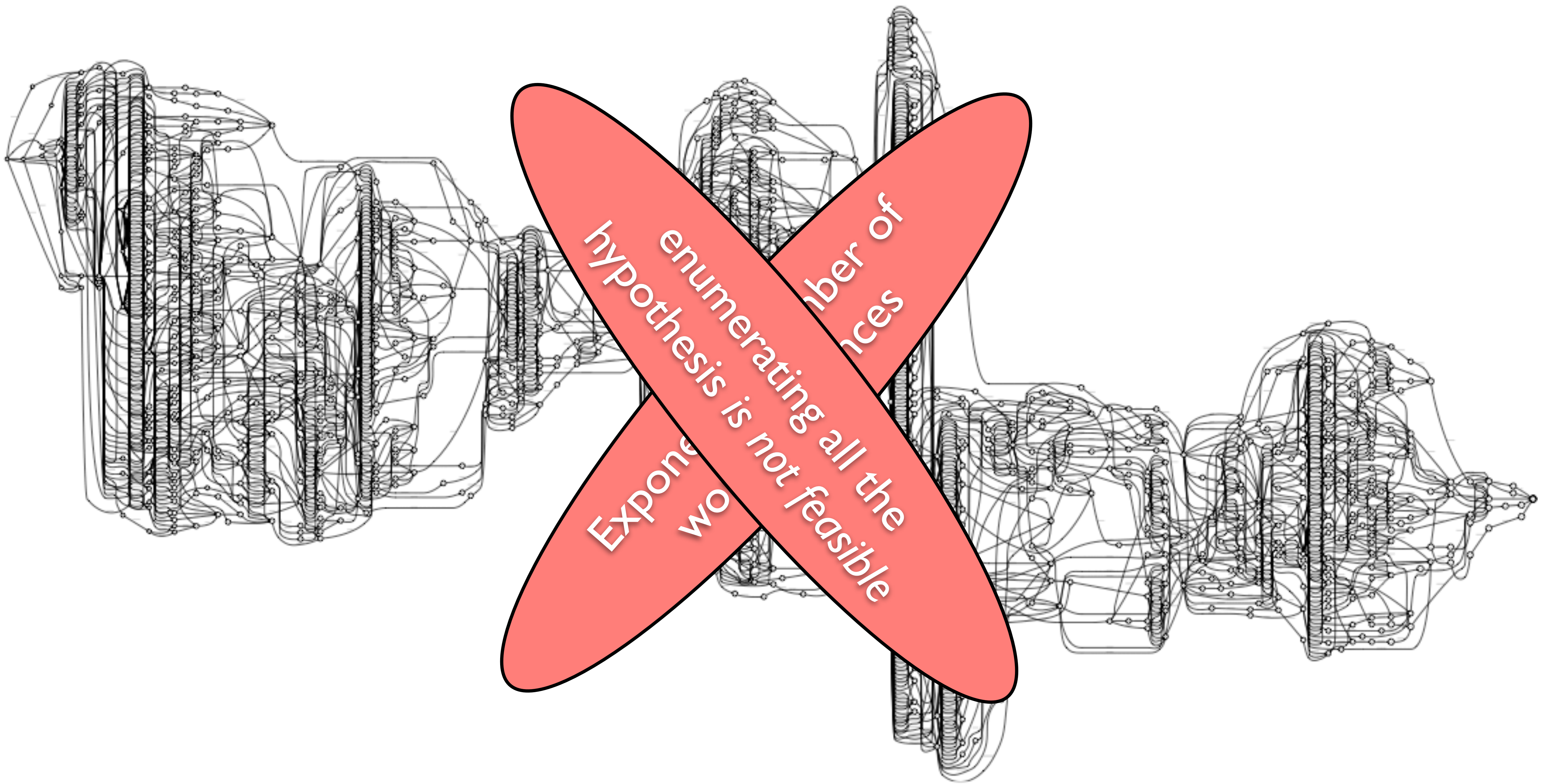

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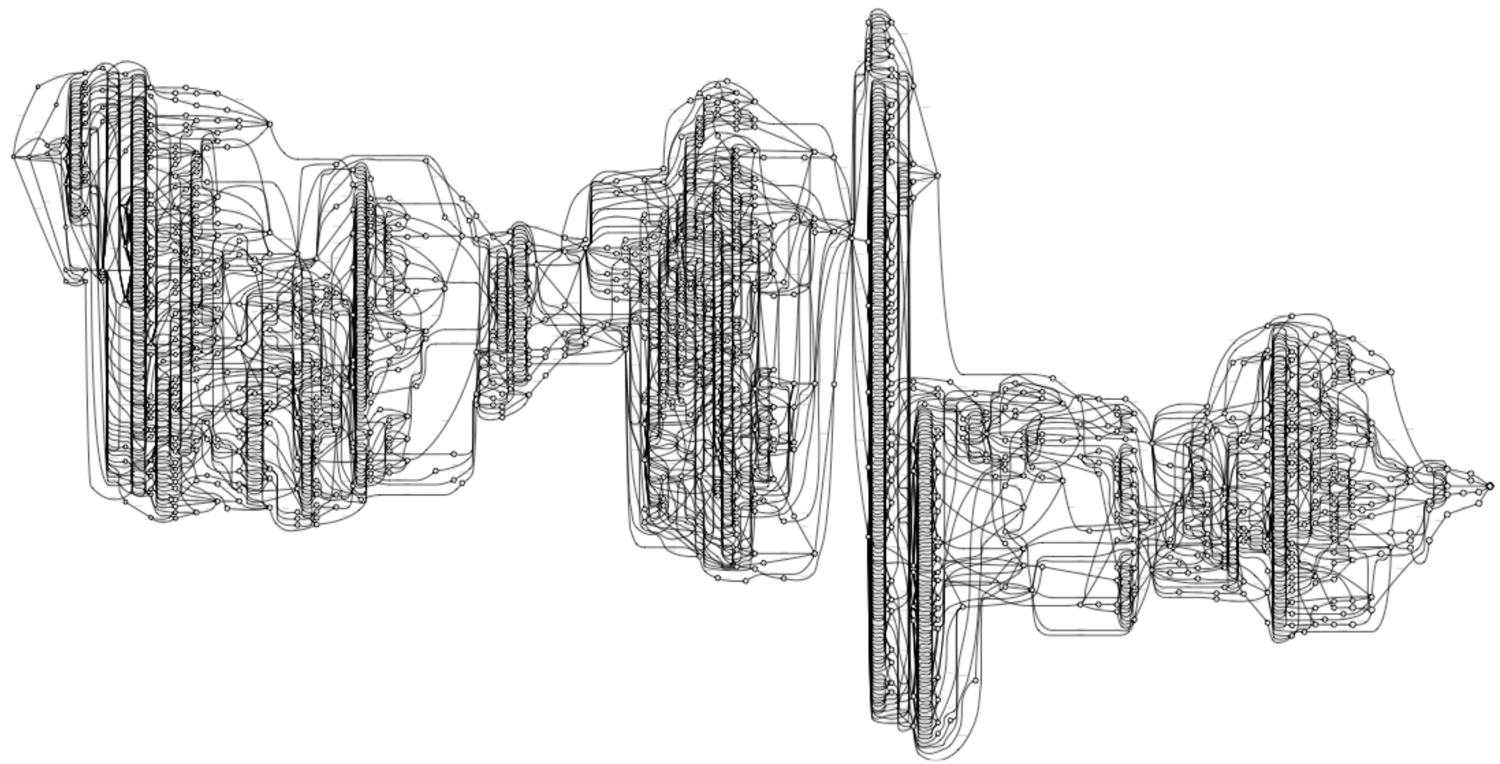
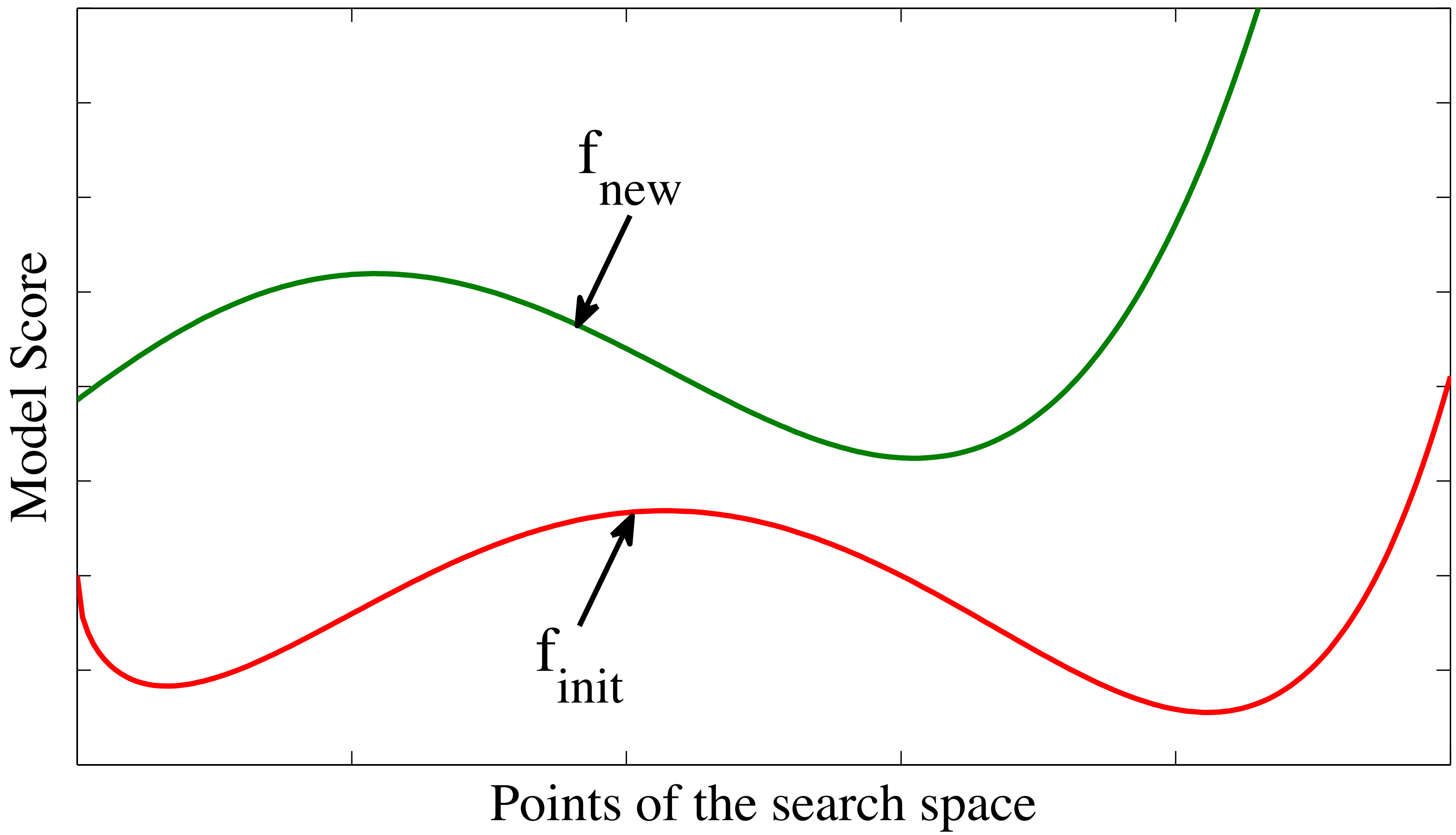


- Instead, *N-best rescoring* strategy is employed
  - Enumerating over the list of *N* best hypotheses (w.r.t the initial model)
- *N-best rescoring* suffers from known *deficiencies* and *inefficiencies*

Motivation

N-best rescoring is not a smart strategy!



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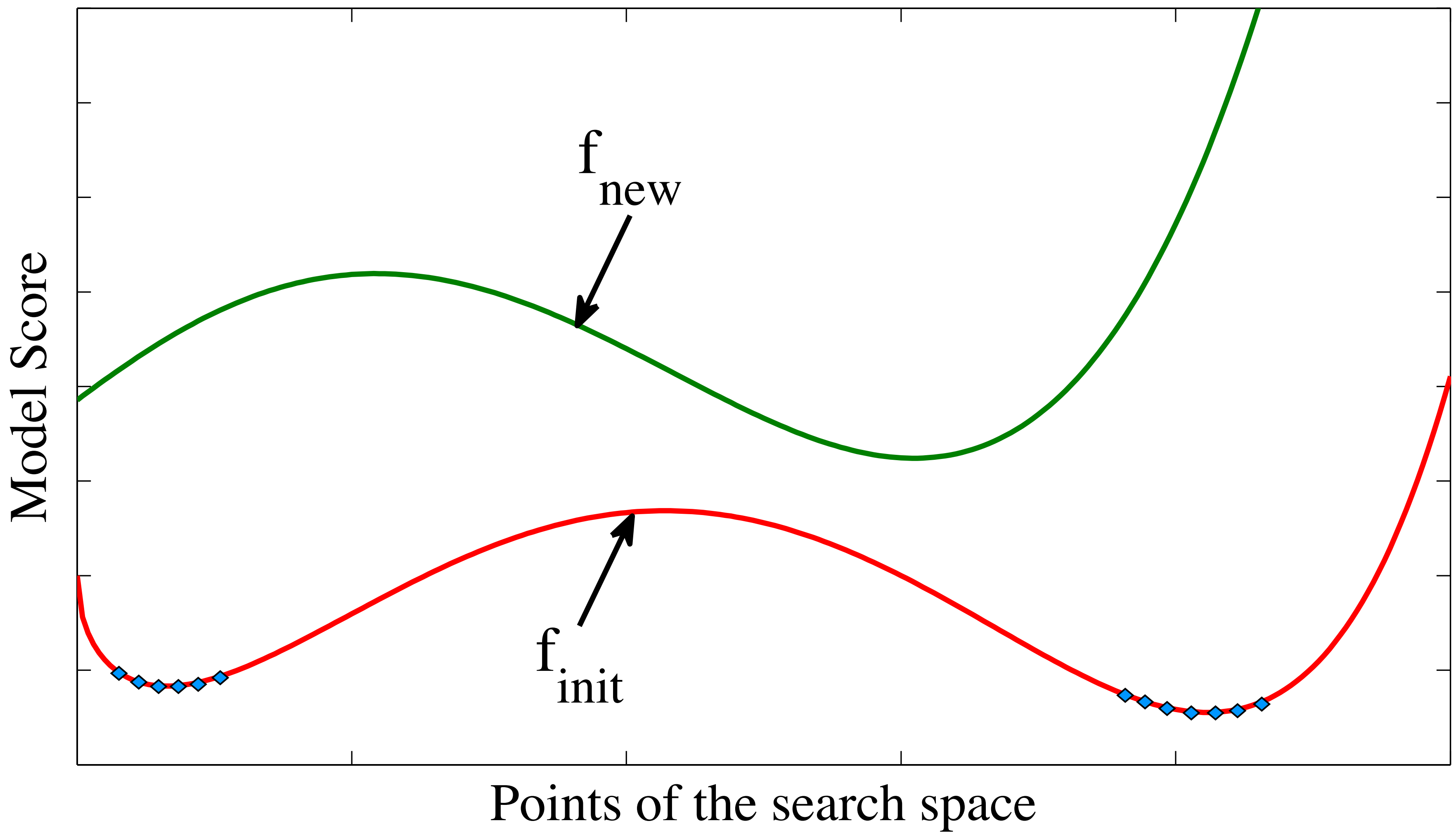

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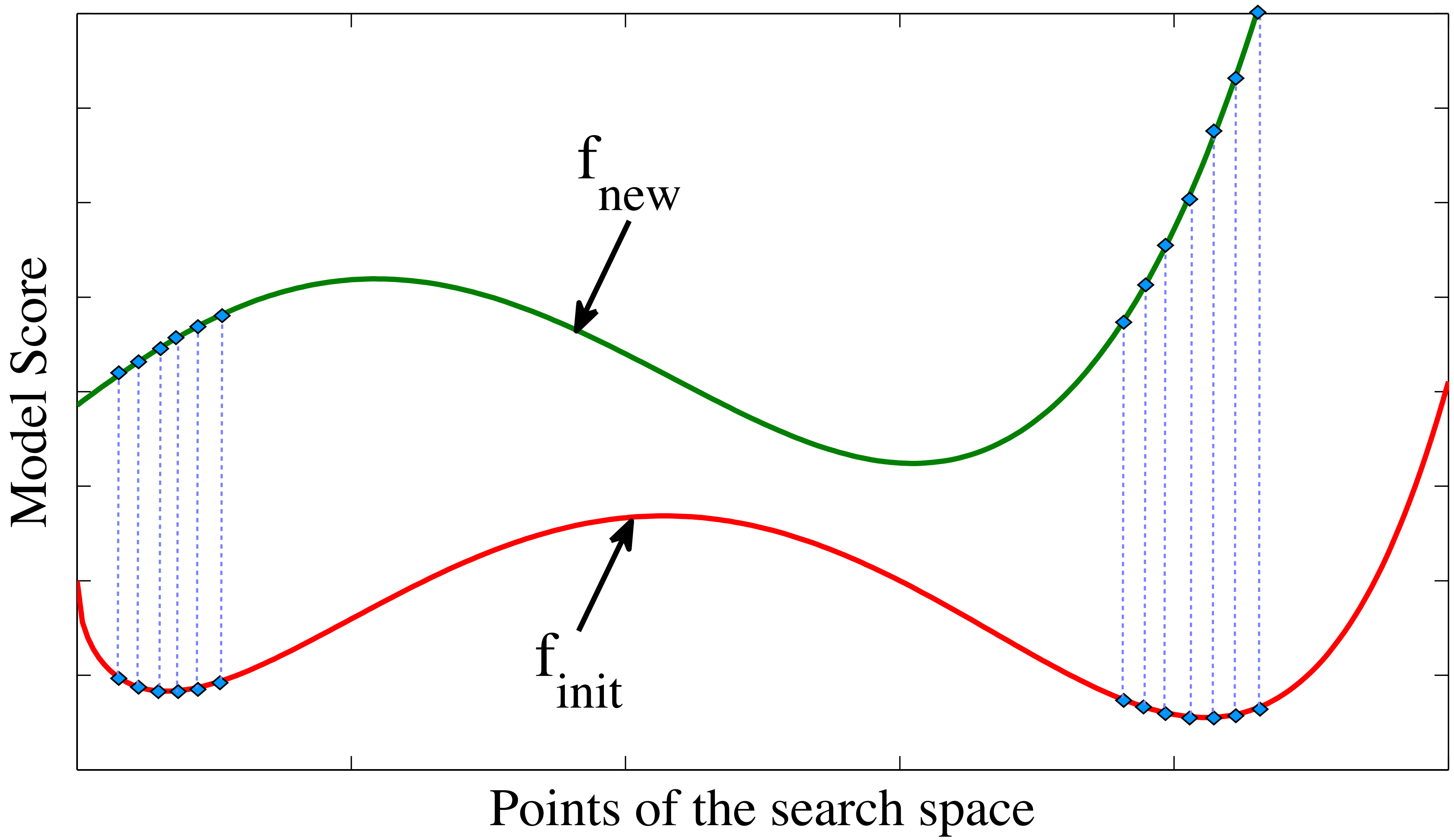
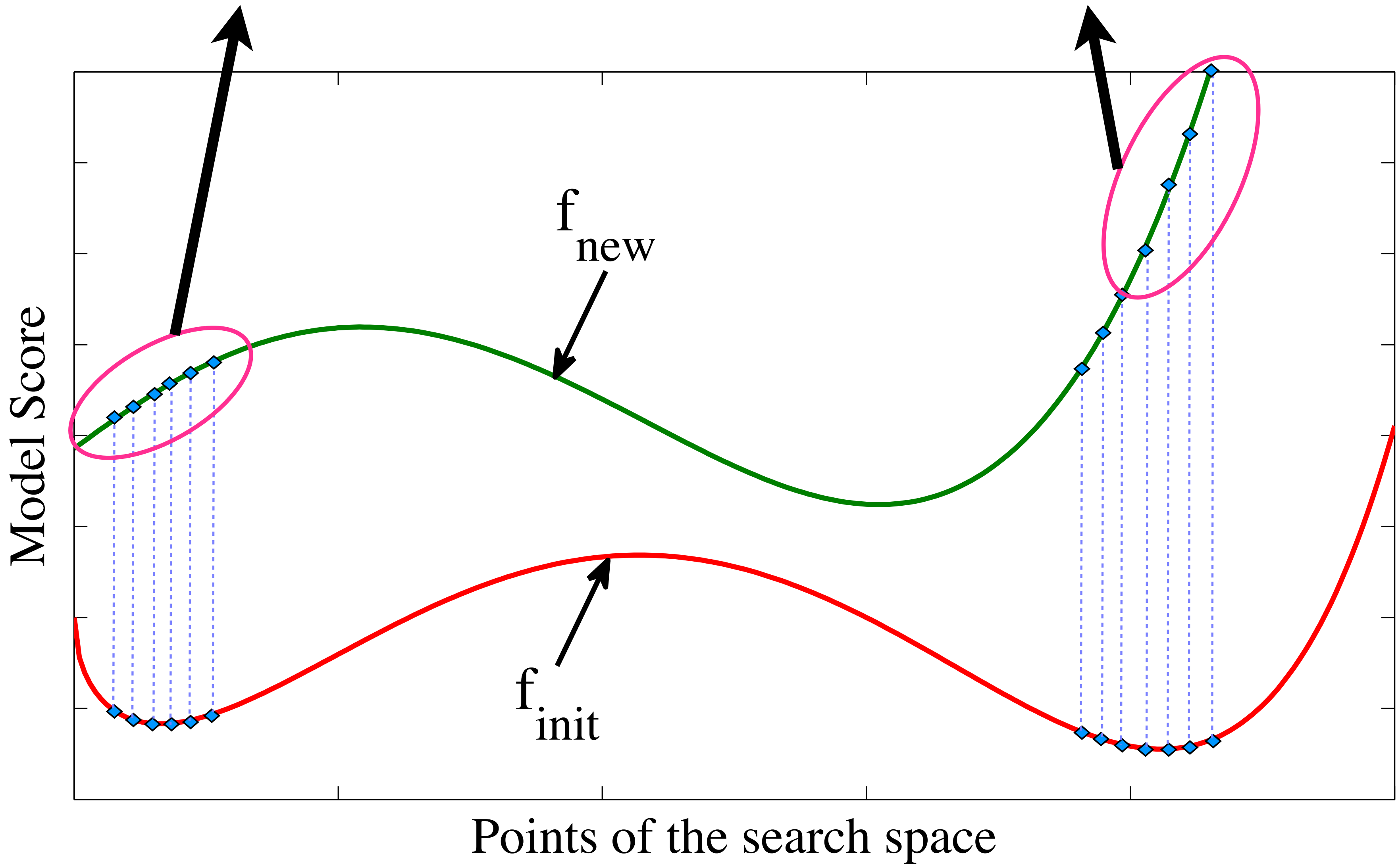


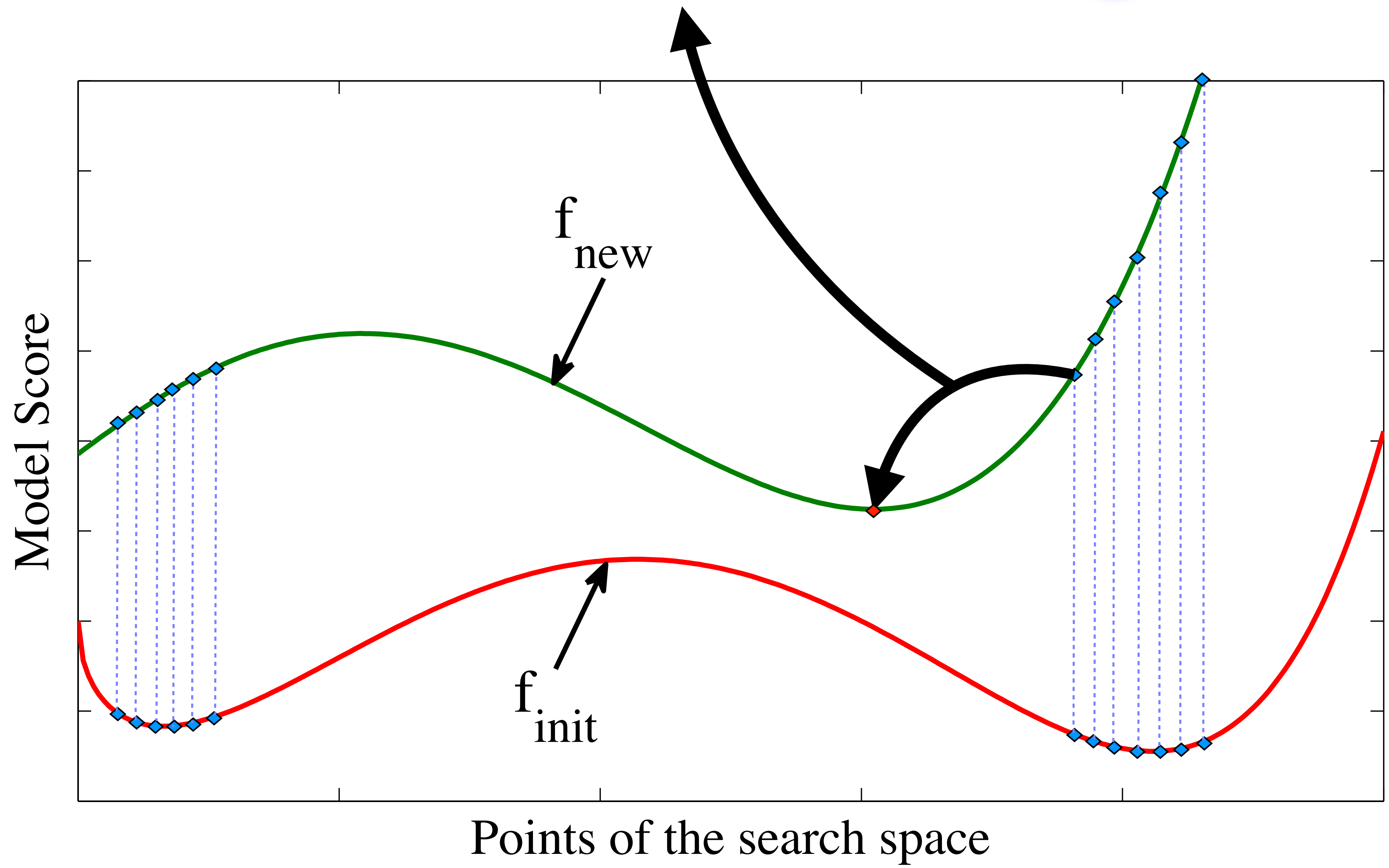
Motivation

Selected points *need not* be representing the best points of the *rescoring* model, in the search space (lattice)



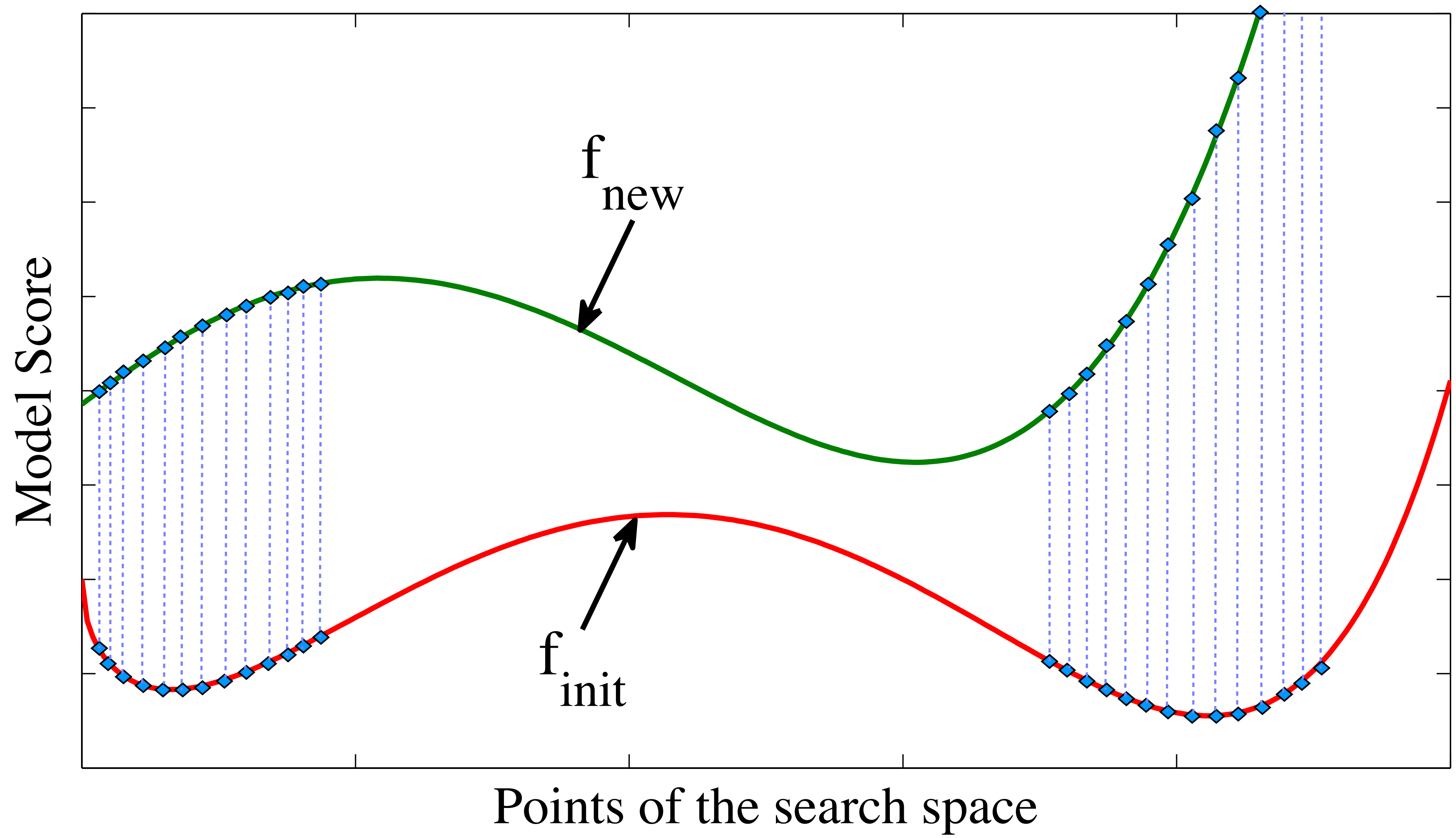
Motivation

search errors for small *N*



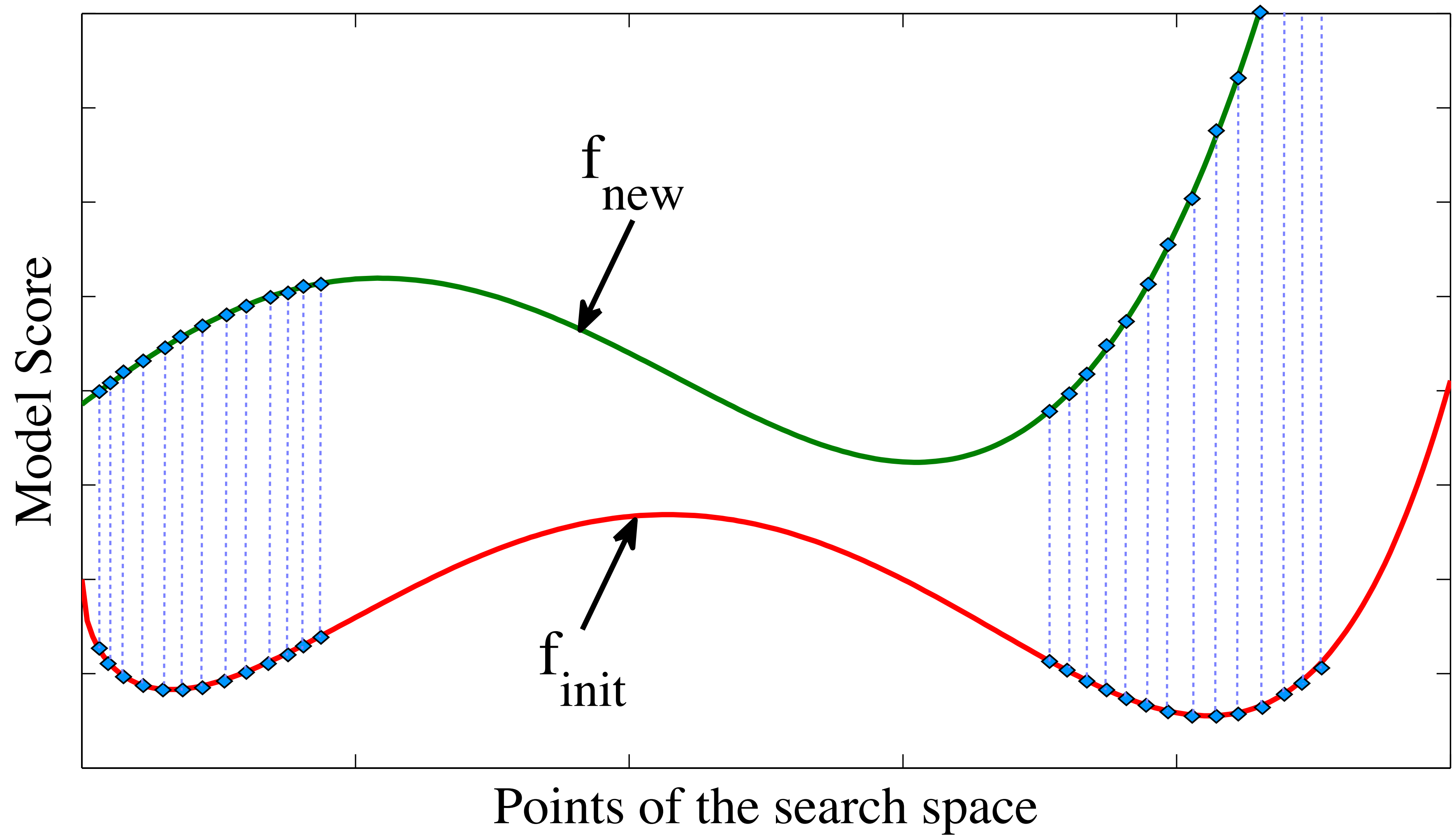
Motivation

N needs to be increased to get closer to the optimal solution.
But ....



Motivation

Considering a large *N* makes the rescoring **computationally expensive**



Motivation

Our Solution:

Use the more complex model to aid hypotheses selection, as opposed to considering the *N* hypotheses chosen by the simpler model

Motivation

Our Solution:

Motivation

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Hill Climbing on speech lattices

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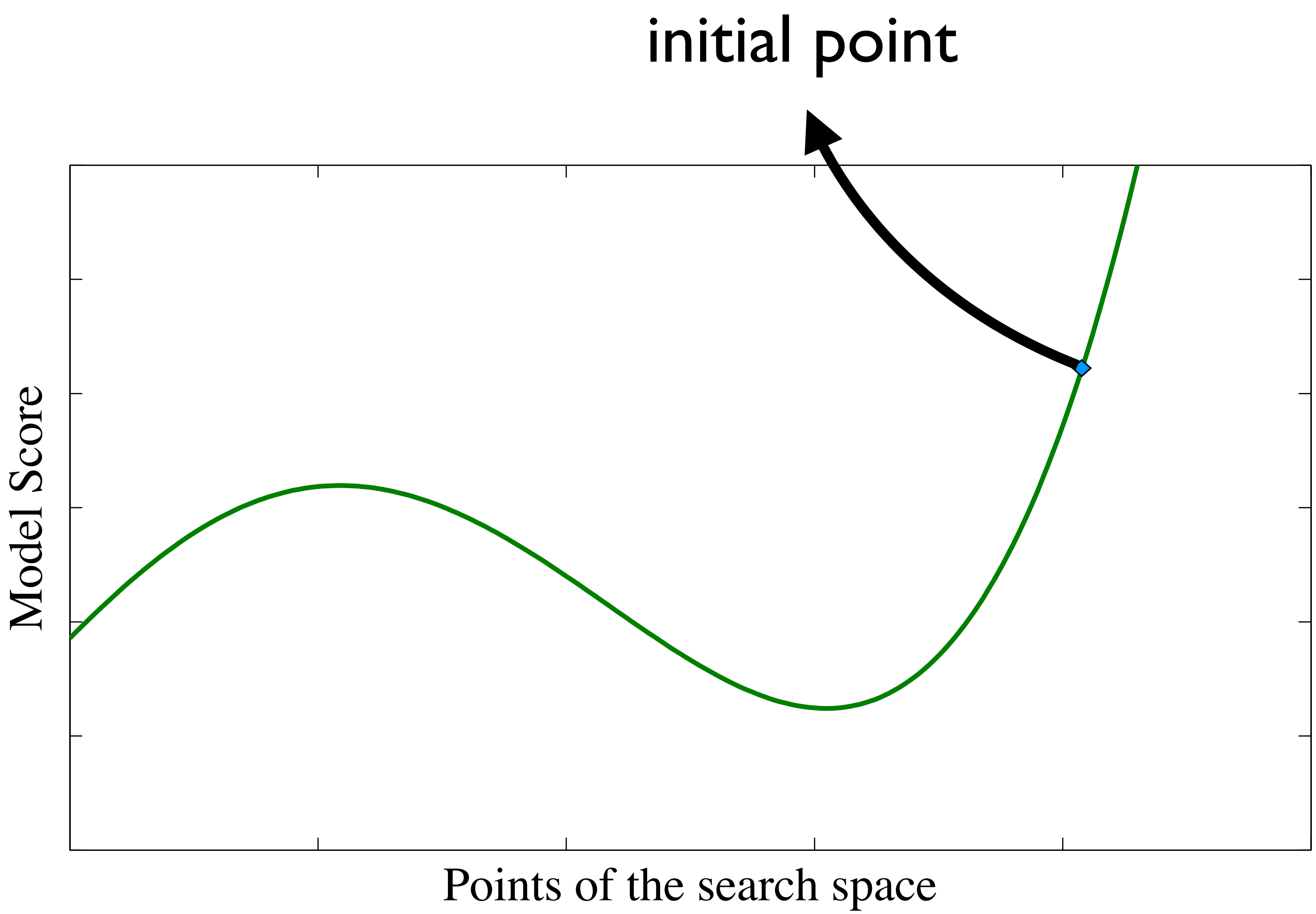
Hill Climbing on speech lattices 

Hill Climbing

- An iterative improvement search strategy:
    i. Starts with an *initial solution* in the search space
    ii. Examines a *neighborhood* of the initial point and steps to the best point in the *neighborhood* (objective function is increasing most steeply)
    iii. Iterates the procedure for the new selected point
    iv. Stops when the current solution *can not* be further improved
- For a broad class of problems, hill climbing is guaranteed to reach a *local maximum* solution

Hill Climbing



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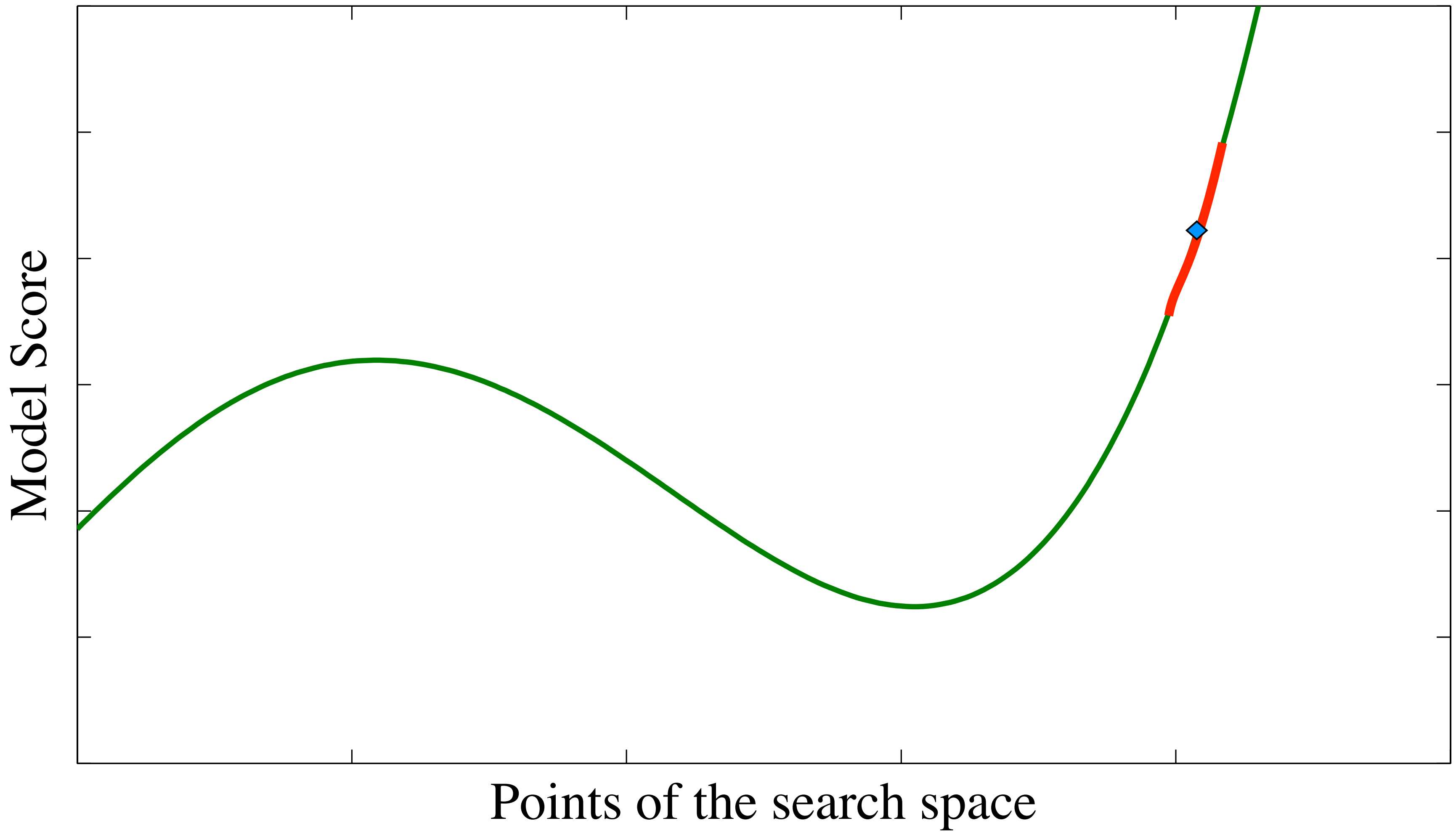

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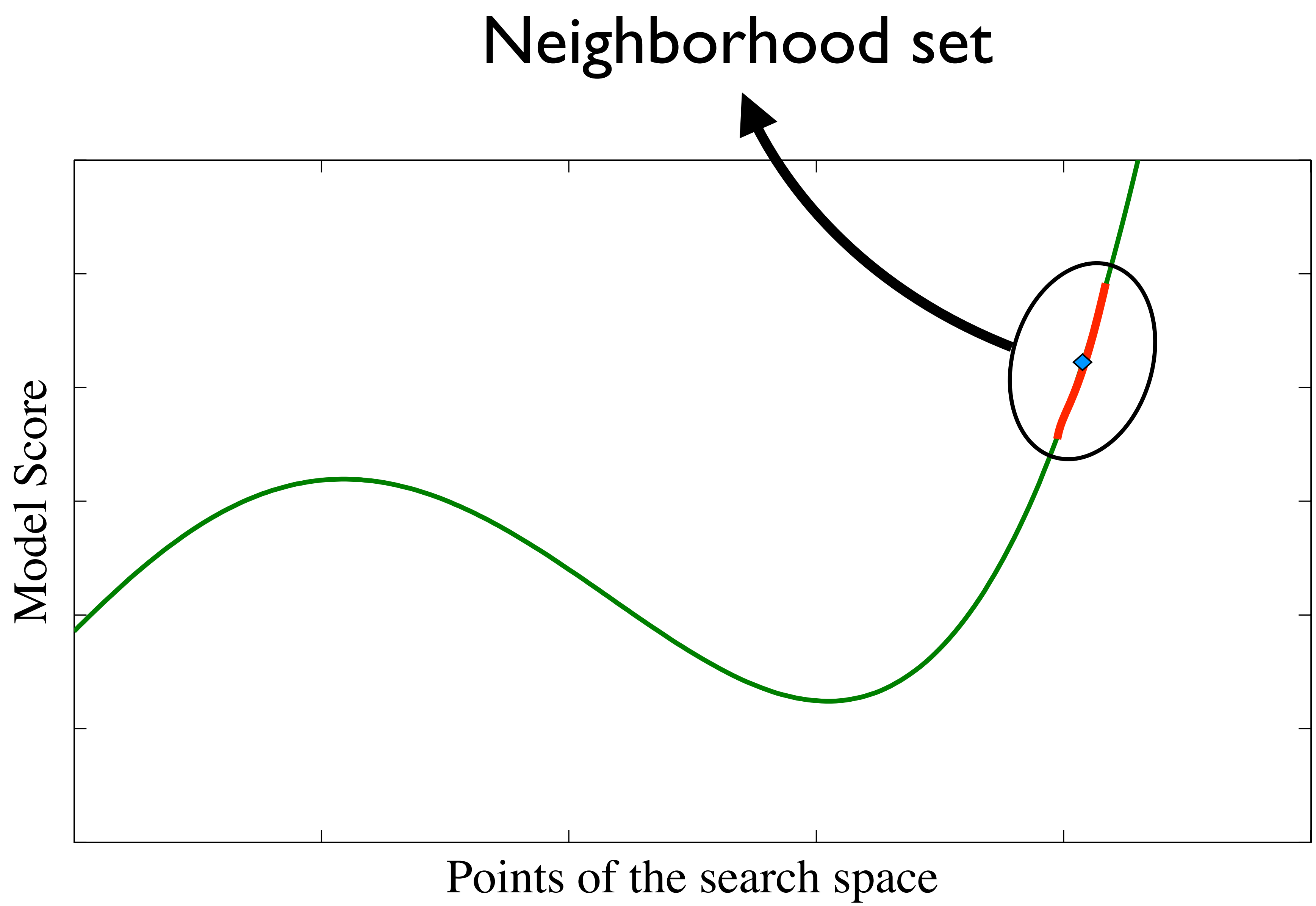

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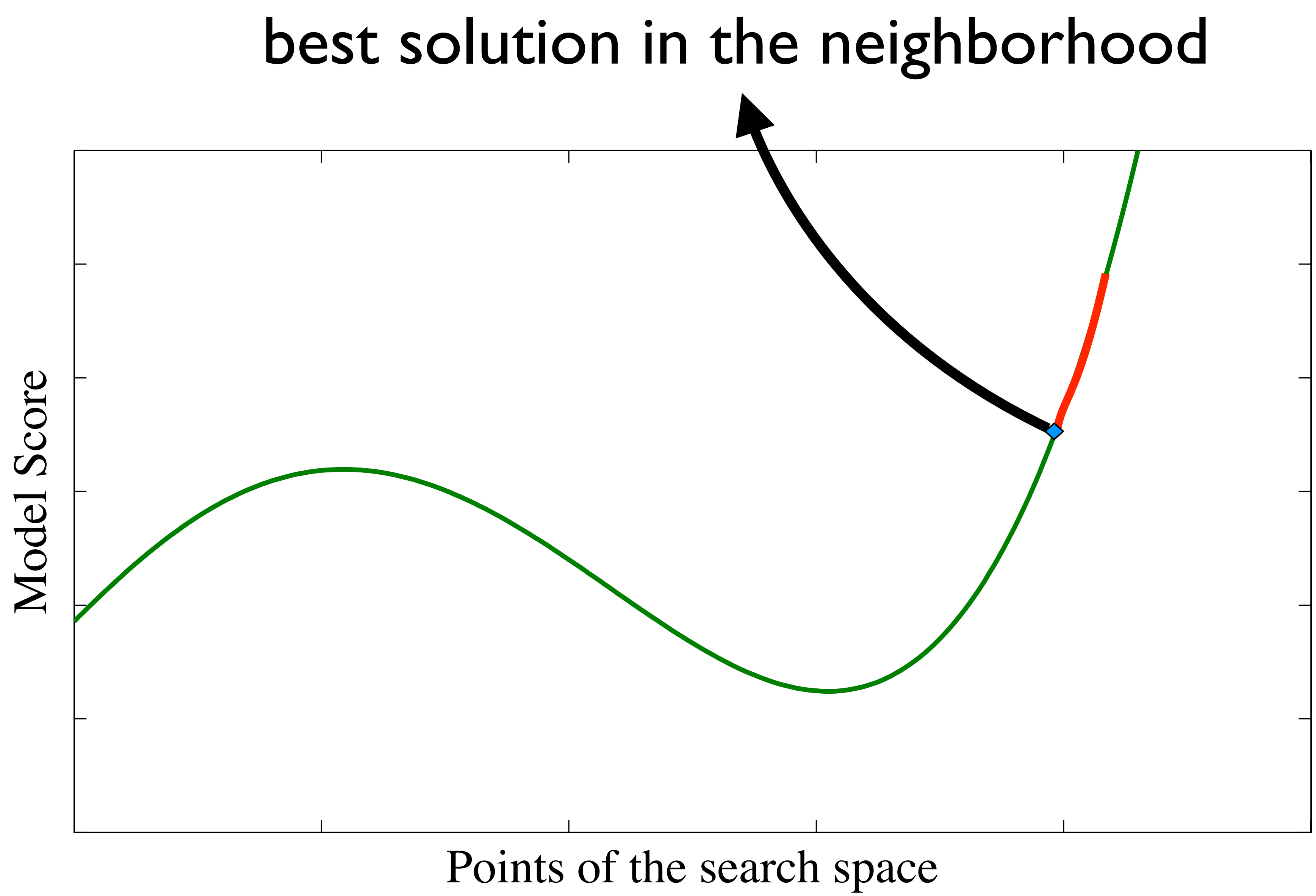

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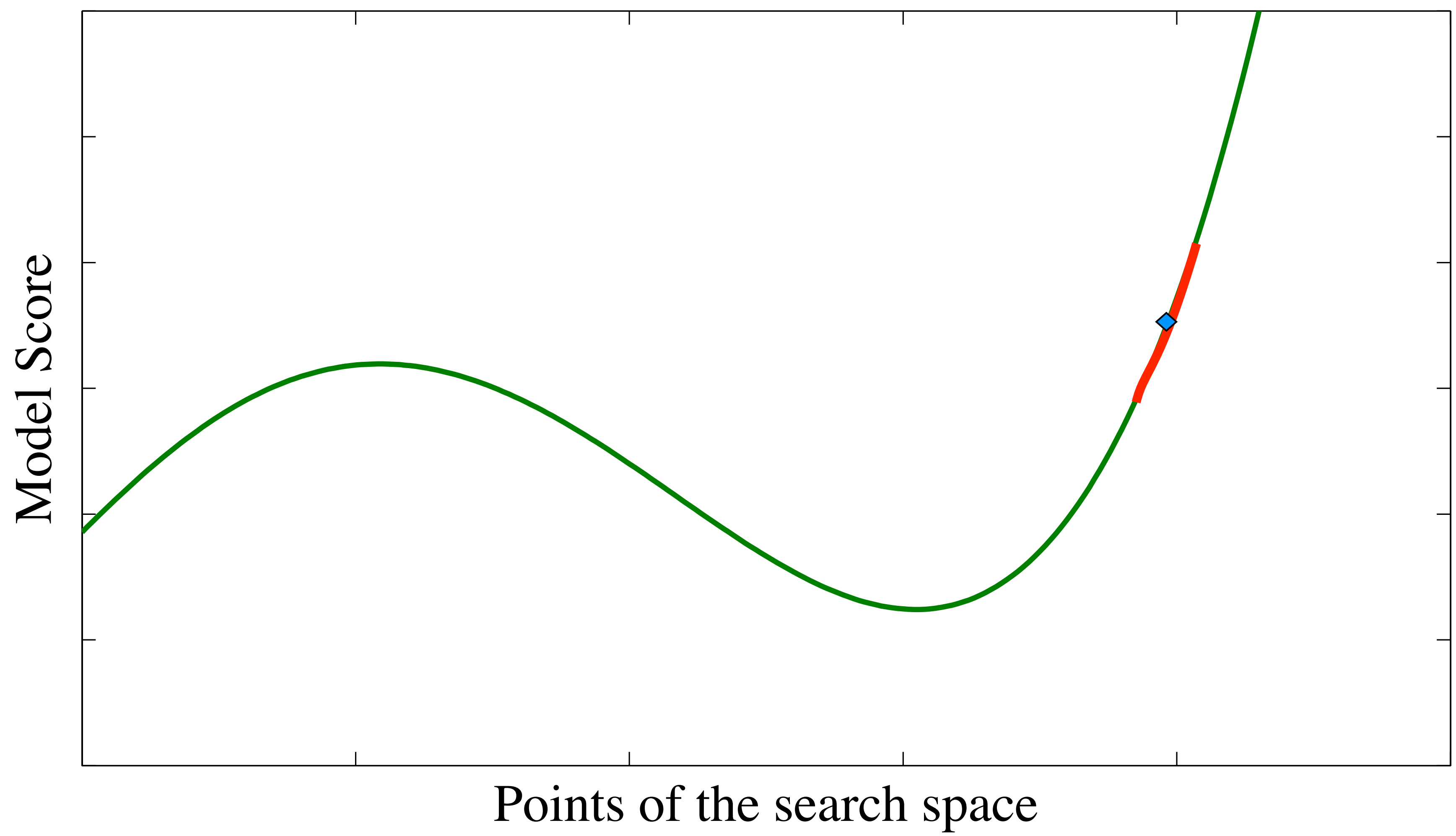

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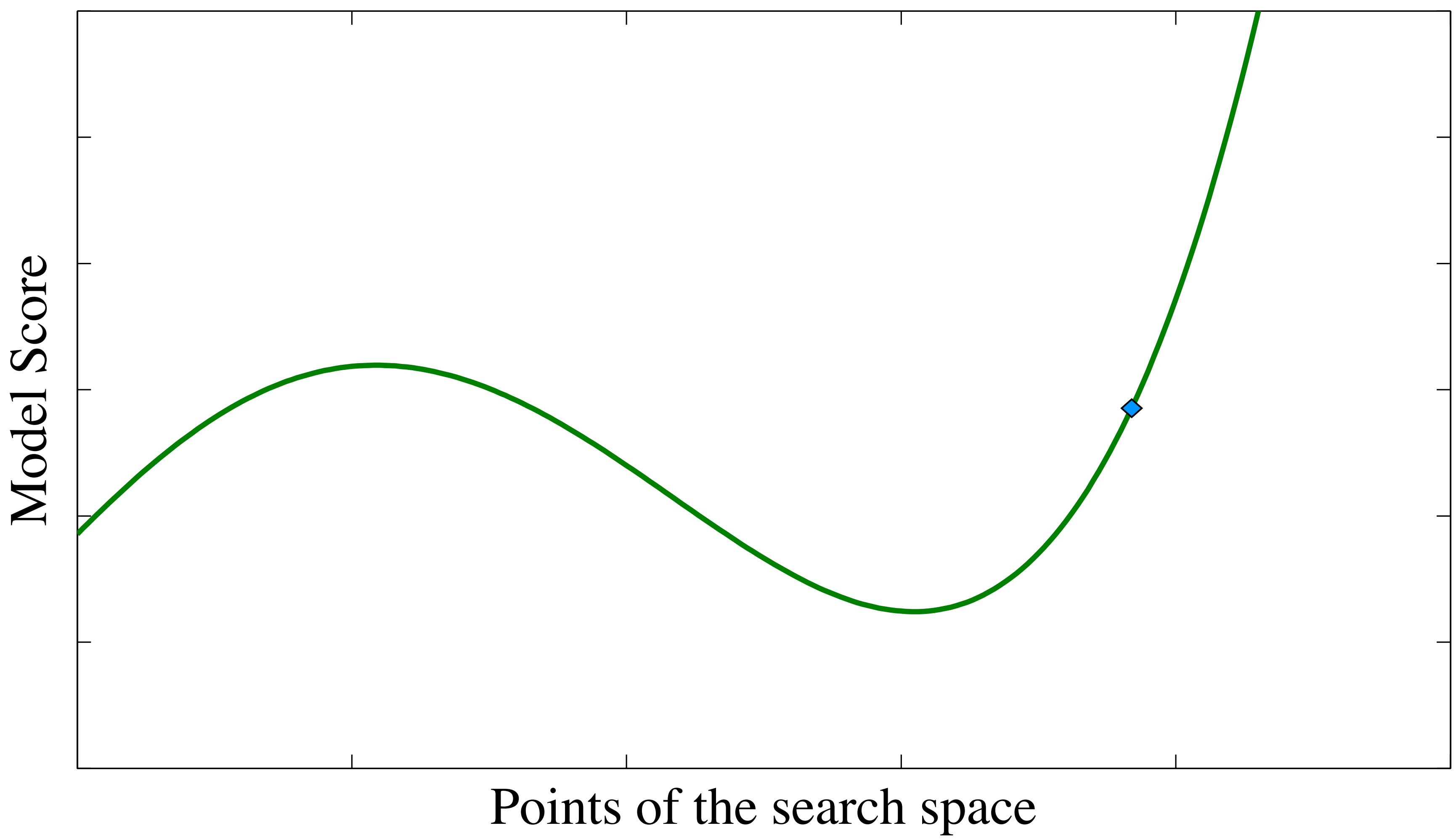

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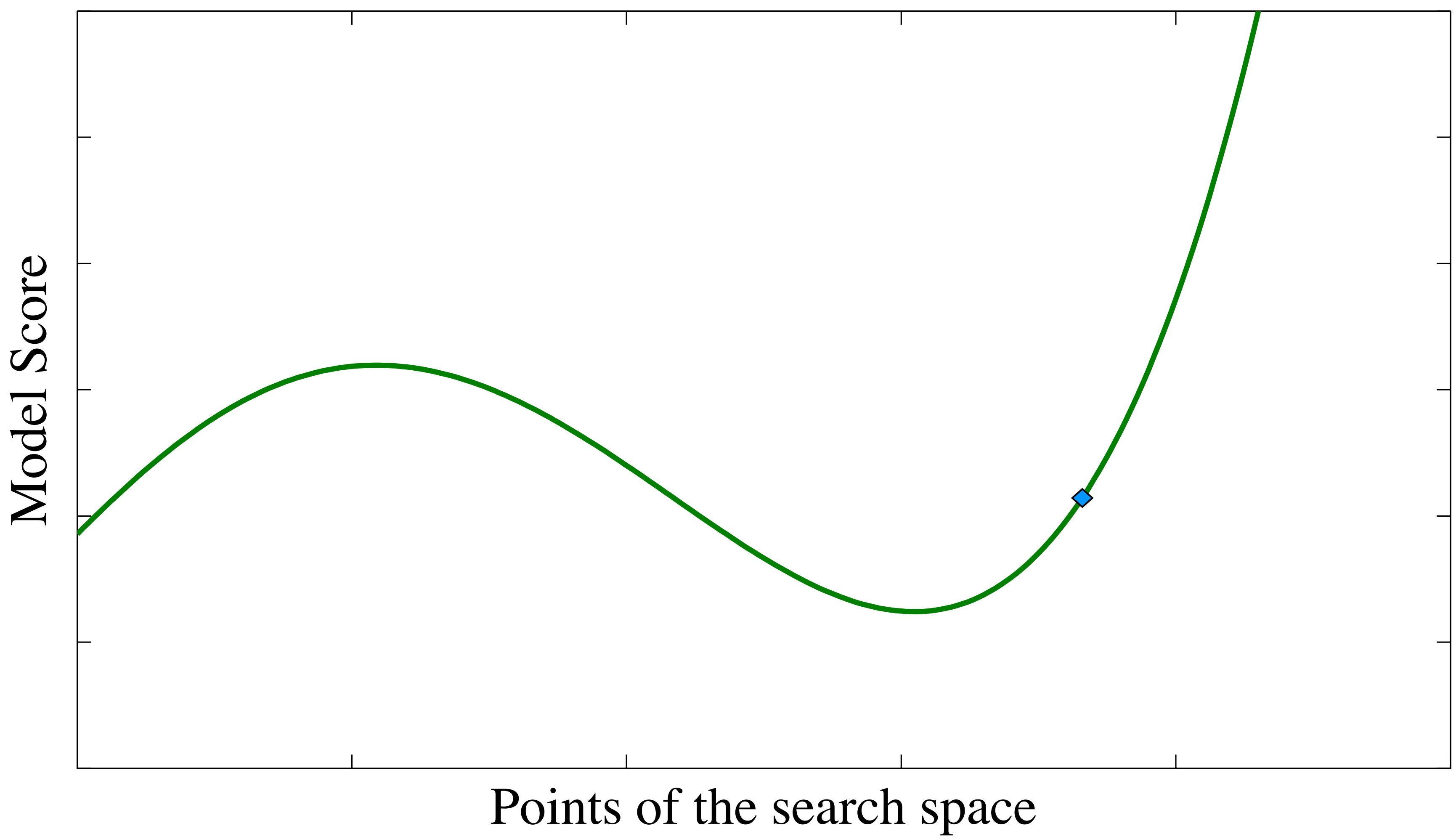

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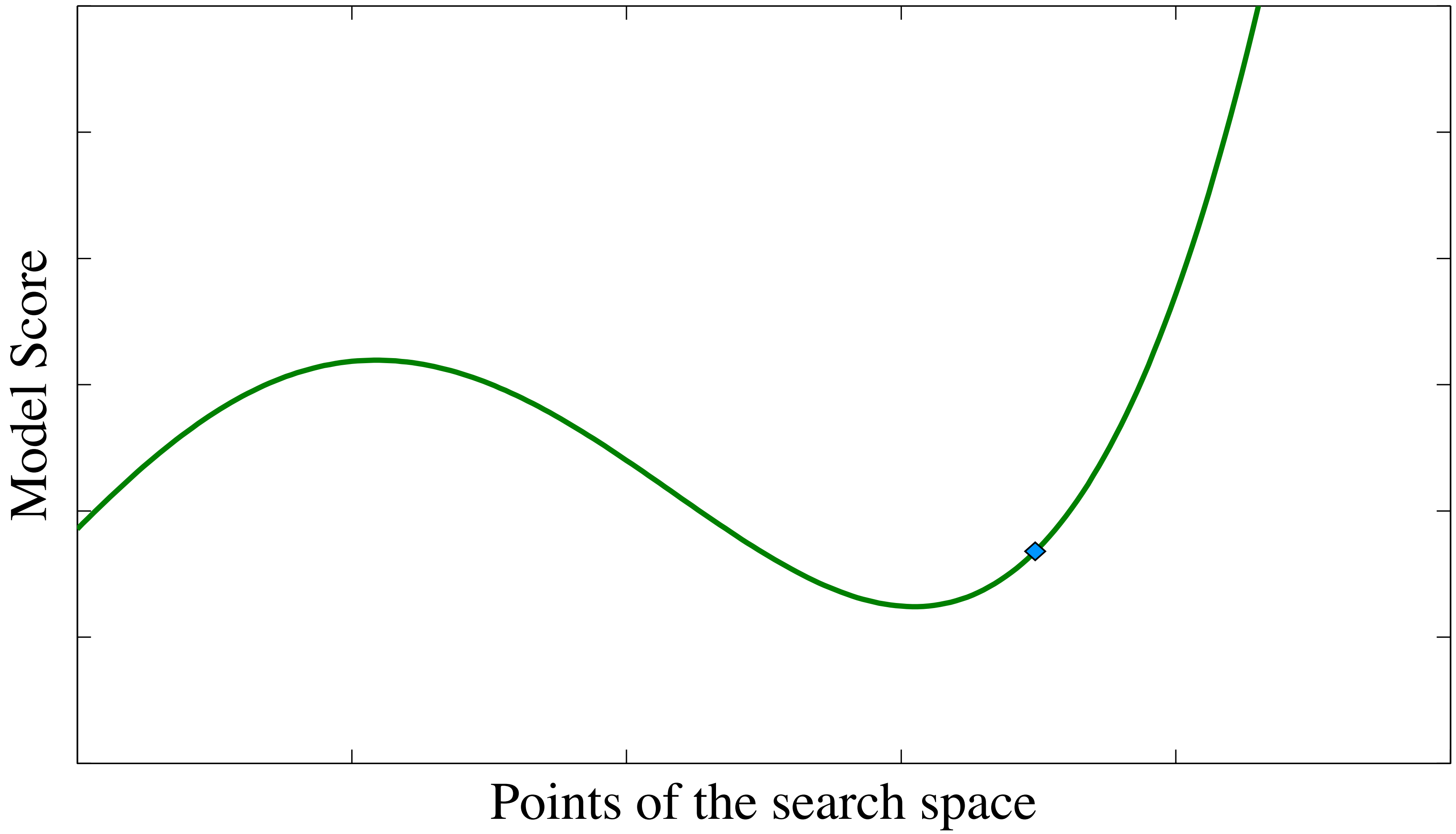

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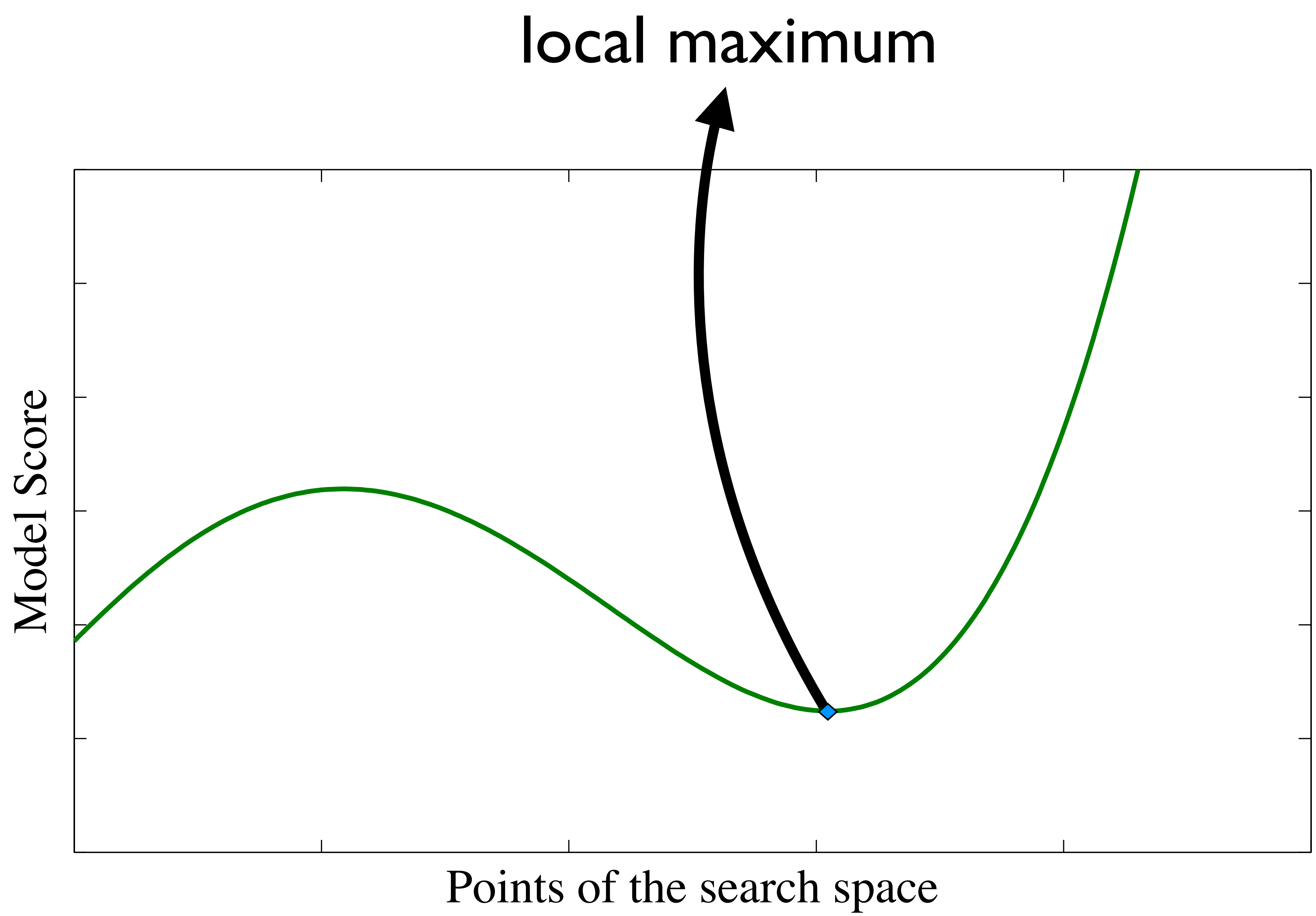

Hill Climbing on Speech Lattices

- The search space consists of set of word-sequences

$$◆ \quad \Rightarrow w_1 w_2 \cdots w_n \in L$$

  - It is natural to define the neighborhood function using the *edit-distance* function

- Specifically, the neighborhood set is defined by editing at specific position *i* of word sequence *W*
  - This neighborhood is represented by $\mathcal{N}(W, i)$
  - deleting, substituting or inserting a word to the left of w_i

- How to generate $\mathcal{N}(W, i)$ efficiently? (will be explained later)

Hill Climbing on Speech Lattices

- In this work, we use hill climbing for LM rescoring
  - The lattice-generating LM is replaced with a long-span/complex LM
  - We gradually climb the search space (word-sequences in the lattice) to maximize:

$$g(X, W; \Lambda, \Gamma_{\text{new}}) = \alpha \log P(X|W, \Lambda) + \log P(W|\Gamma_{\text{new}})$$

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The evaluation method of the new LM is called

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$i \leftarrow i + 1$

$$g(X, W'; \Lambda, \Gamma_{\text{new}}) = \alpha \log P(X|W', \Lambda) + \log P(W'|\Gamma_{\text{new}})$$

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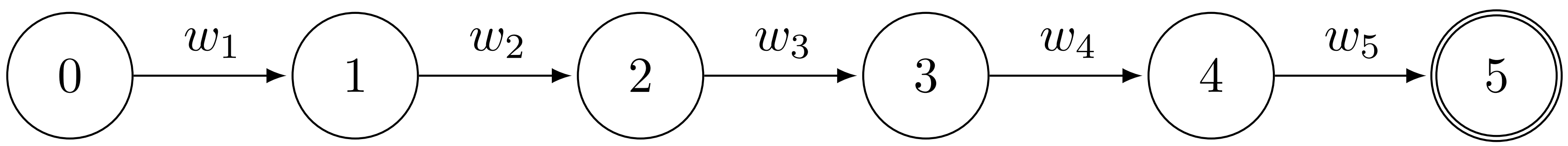
Efficient Generation of Neighborhoods

1

- The set of all word sequences that can be generated from *W* with *one deletion, insertion or substitution* can be represented by a **FSA** .
  - Let us call this machine $LC(W, i)$
- We will illustrate how $LC(W, i)$ can be constructed through an example

Efficient Generation of Neighborhoods

$$W = w_1 w_2 w_3 w_4 w_5$$



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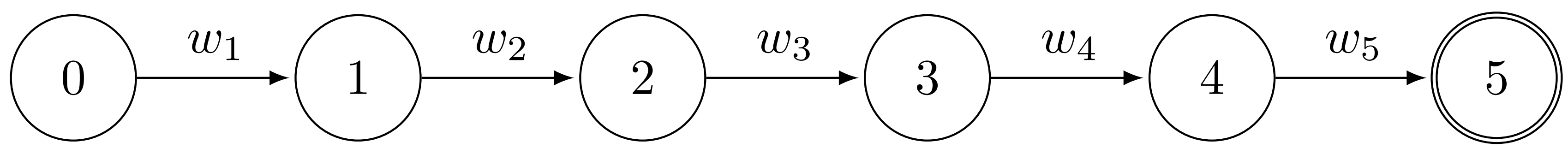
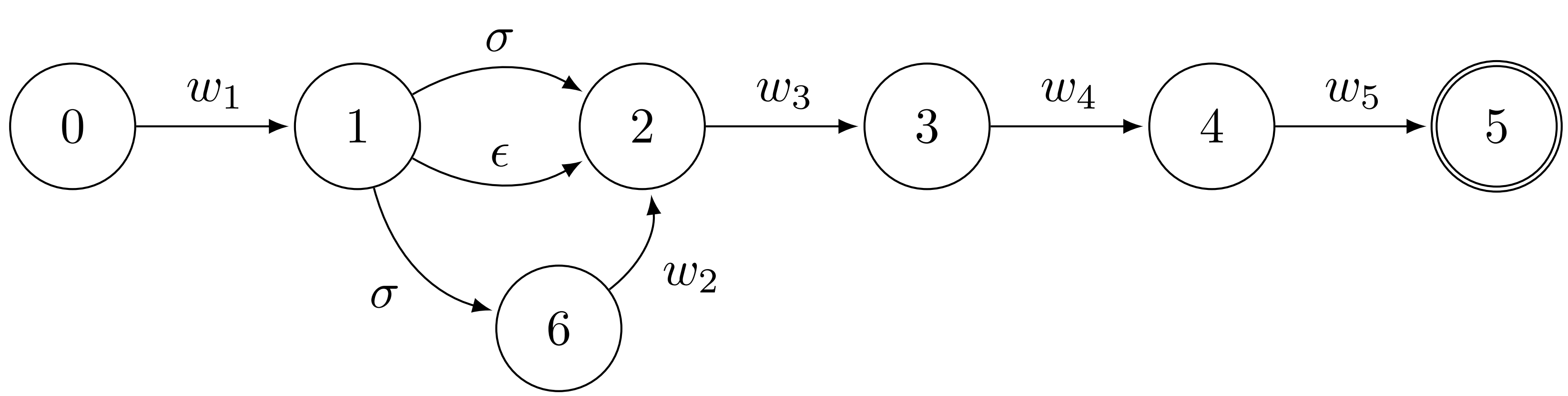


$$LC(W, 2)$$



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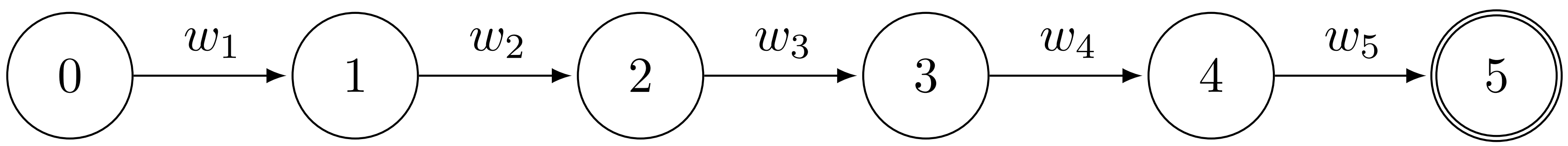

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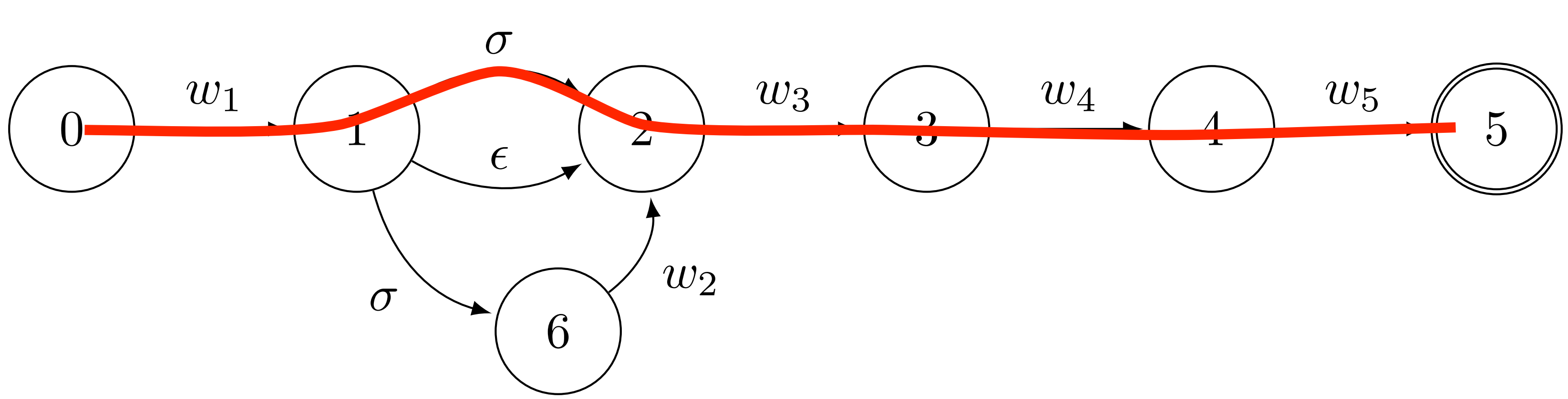
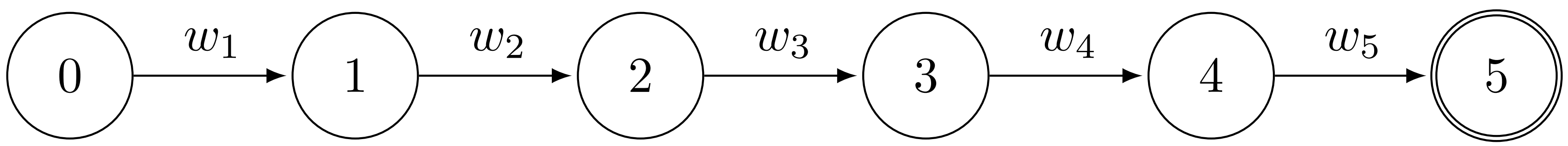


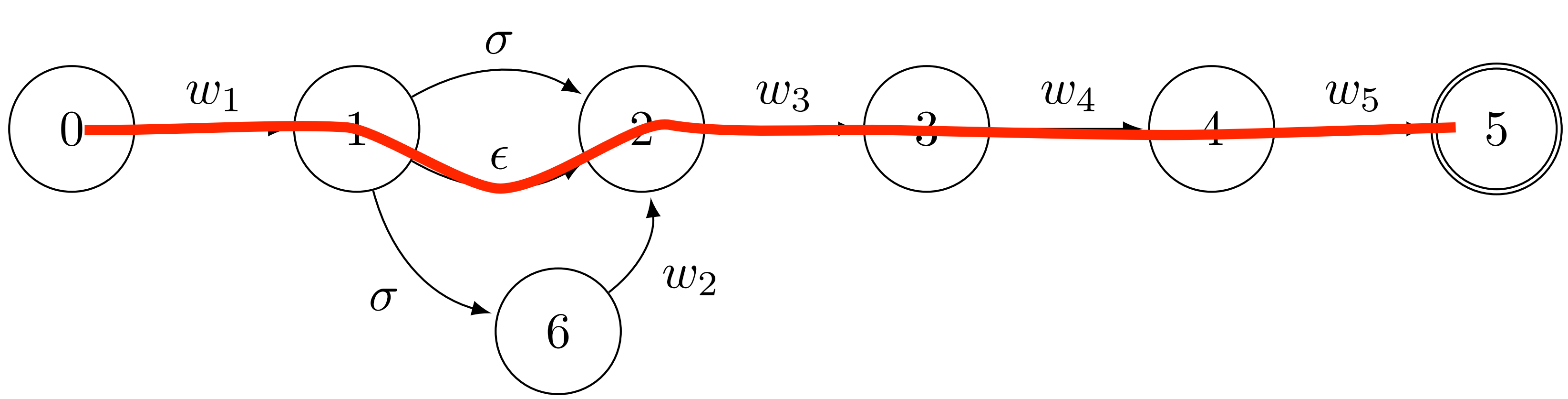
Substitutions

Efficient Generation of Neighborhoods

$$W = w_1 w_2 w_3 w_4 w_5$$



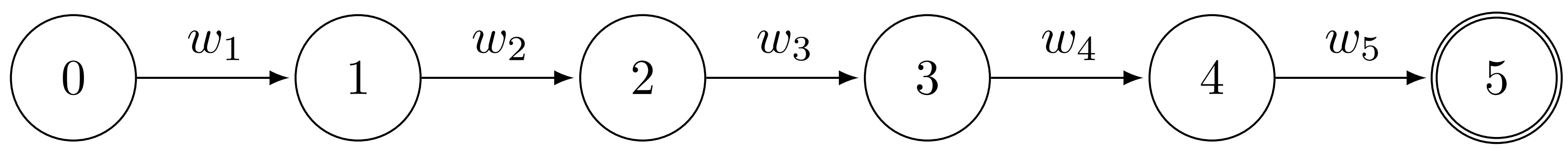
$$LC(W, 2)$$



deletion

Efficient Generation of Neighborhoods

$$W = w_1 w_2 w_3 w_4 w_5$$



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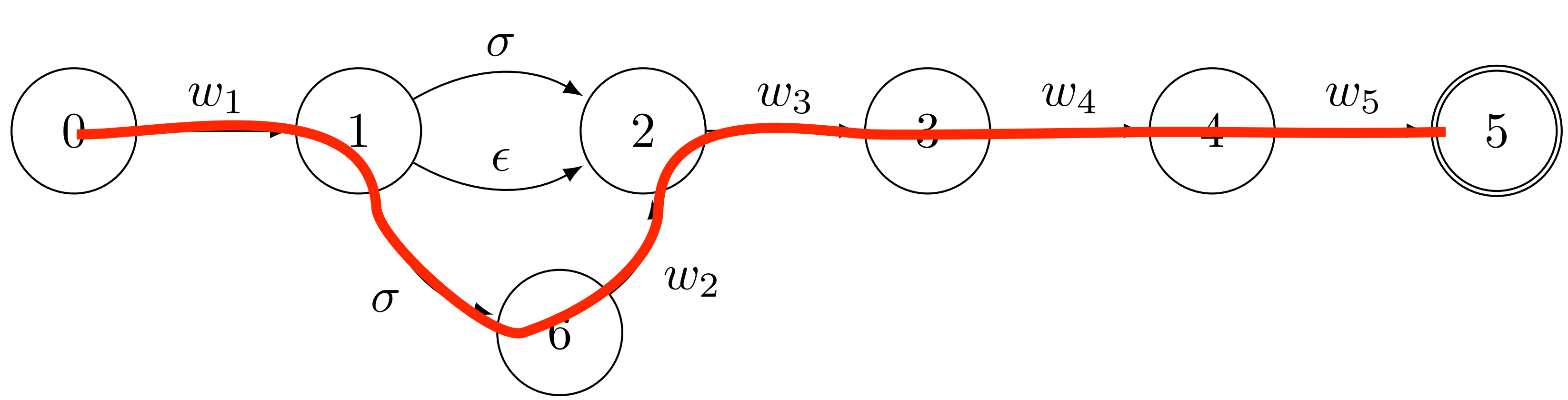
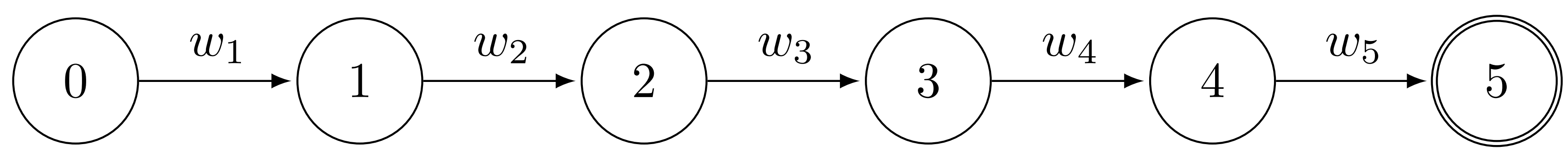


insertions (to the left)

Efficient Generation of Neighborhoods

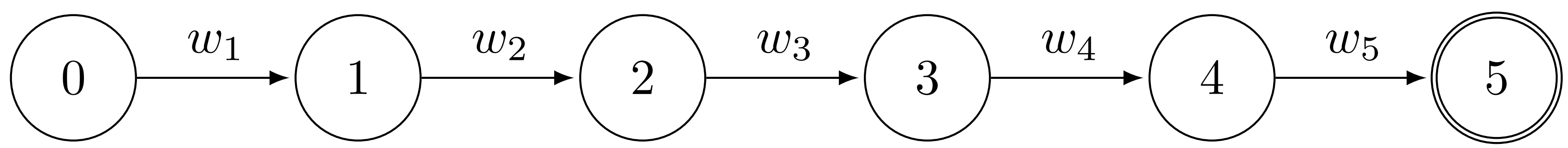
$$W = w_1 w_2 w_3 w_4 w_5$$



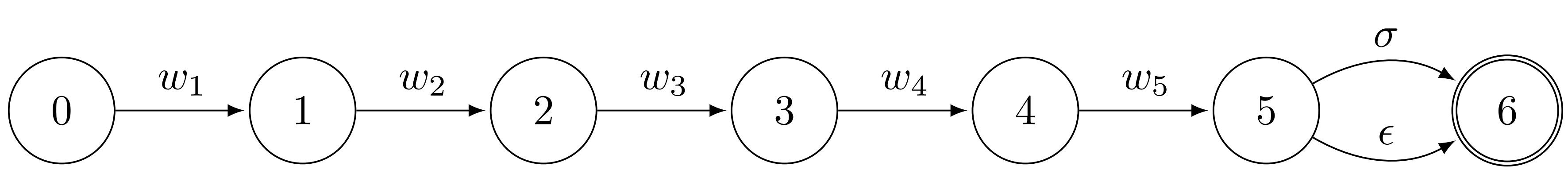
- Due to the arbitrary decision to insert only to the left of a position, we also define $LC(W, n+1)$ which permits insertions to the *right of the last word*

Efficient Generation of Neighborhoods

$$W = w_1 w_2 w_3 w_4 w_5$$



$$LC(W, 6)$$



insertions (at the end)

Efficient Generation of Neighborhoods

2

- To *restrict* the neighboring set to *word sequences in the lattice* (our search space), $LC(W, i)$ is intersected with a weighted FSA representation of the lattice, L_{acoustic}:

$$LN(W, i) \leftarrow LC(W, i) \circ L_{\text{acoustic}}$$

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Acoustic scores are needed to be combined with the new LM score, according to our rescoring Eqn.

Efficient Generation of Neighborhoods

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represents the neighboring set, including the corresponding acoustic scores

Local Maxima

- Our algorithm is not guaranteed to find the *global maximum* and may get stuck in a local maximum solution
  - This is true in general for hill climbing algorithms which are applied to non-convex space
- Two common solutions to overcome this problem:

1. **Random-restart hill climbing:** hill climbing is carried out using different random starting points
2. **Simulated Annealing:** unlike hill climbing it is possible to accept random moves from the neighborhood.

S. Kirkpatrick and et. al, Science 1983

Local Maxima

- In this work, we consider random-restart technique
  - This is true in general for hill climbing algorithms which are applied to non-convex space
- Our hill climbing algorithm is **repeated** *M* times, each time with a different initial word sequence
  - We will have *M* different stoping paths along with their corresponding scores (under the new model)
  - The path with the maximum score is selected as the final output of the algorithm
- The initial paths are selected by **sampling** the initial lattices
  - We make sure sampled paths *are not repeated*
  - For the first iteration, we always start with *viterbi* path

Experimental Setup

- The ASR system is based on the 2007 IBM speech transcription system for GALE
- The initial lattices are generated using a *3-gram* LM with Kneser-Ney smoothing
  - It has about *2.4*M *N-grams* and is built on *400*M *broadcast news* LM training text
- We use two different models for rescoring experiments:
  - *4-gram* LM with about *64*M *N-grams*
  - Model *M* shrinking based exponential LM

S.F. Chen, *NAACL-HLT* 2009

- Results are reported on the following sets:
  - rt04 on which the WER of initial lattices is *15.51%* (using 3-gram LM)
  - dev04f with initial WER of *17.03%*

Evaluation of the Efficacy

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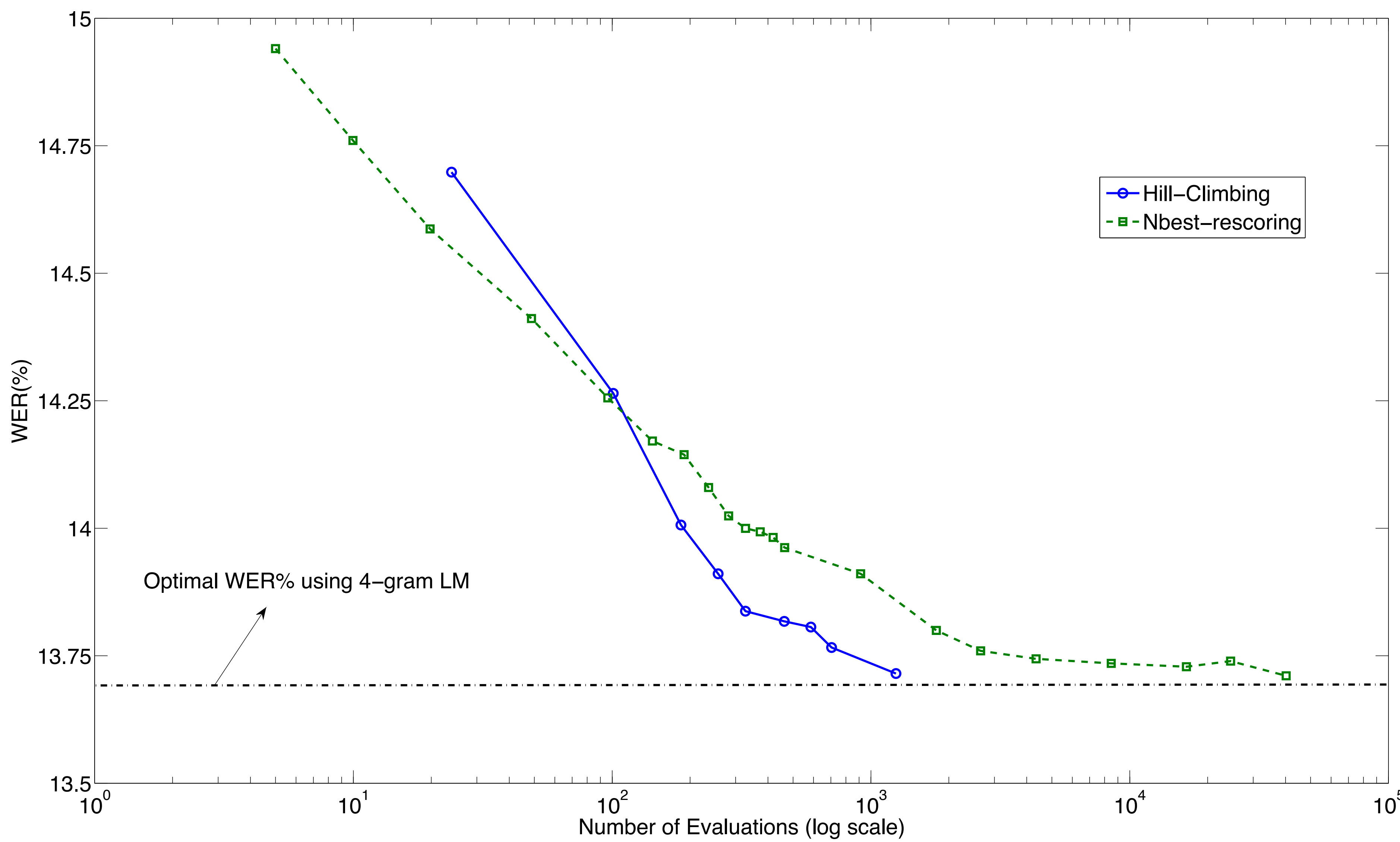
2. The algorithms are also analyzed based on how close they can get to the WER of the optimal solution (global maximum) of the rescoring model

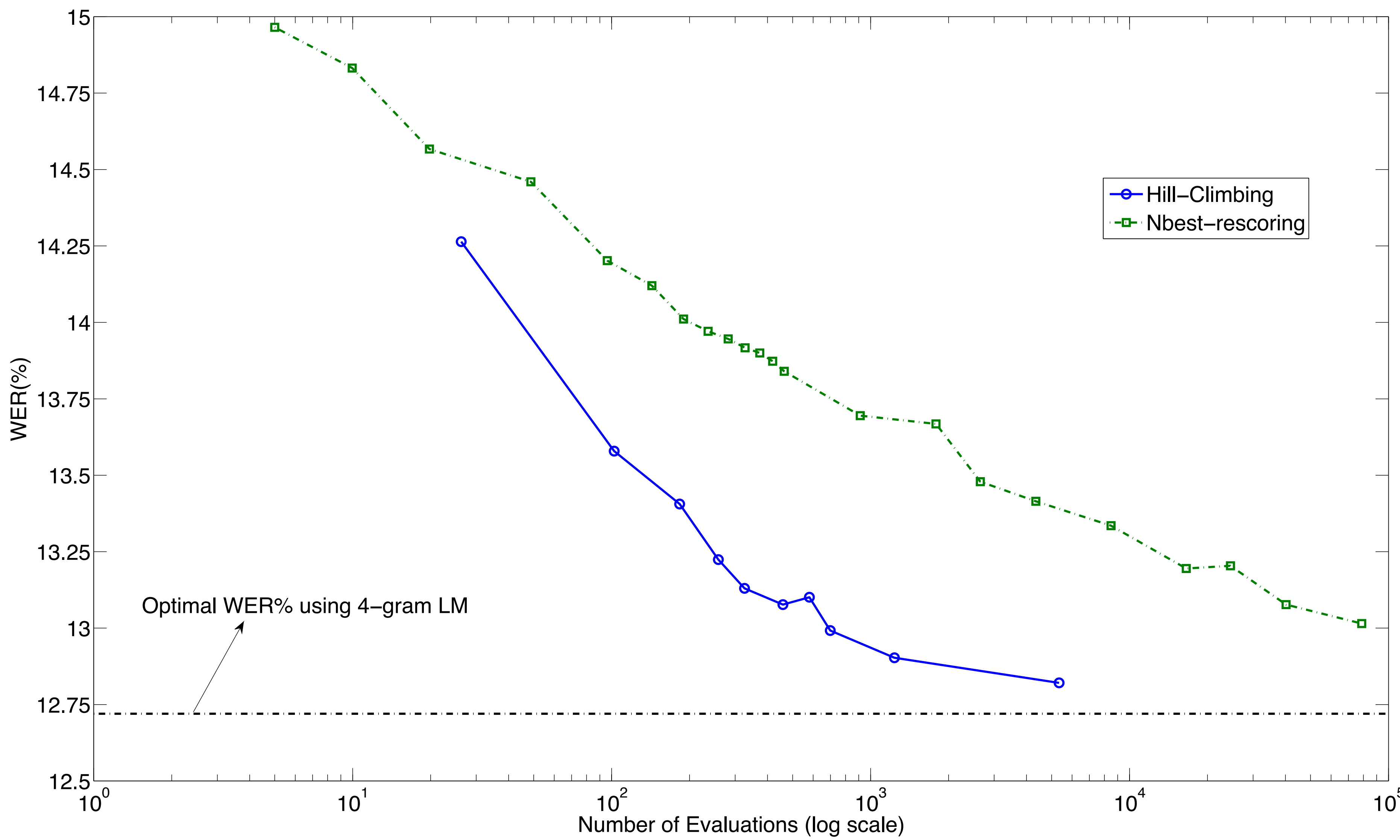
Results

4-gram LM on rt04



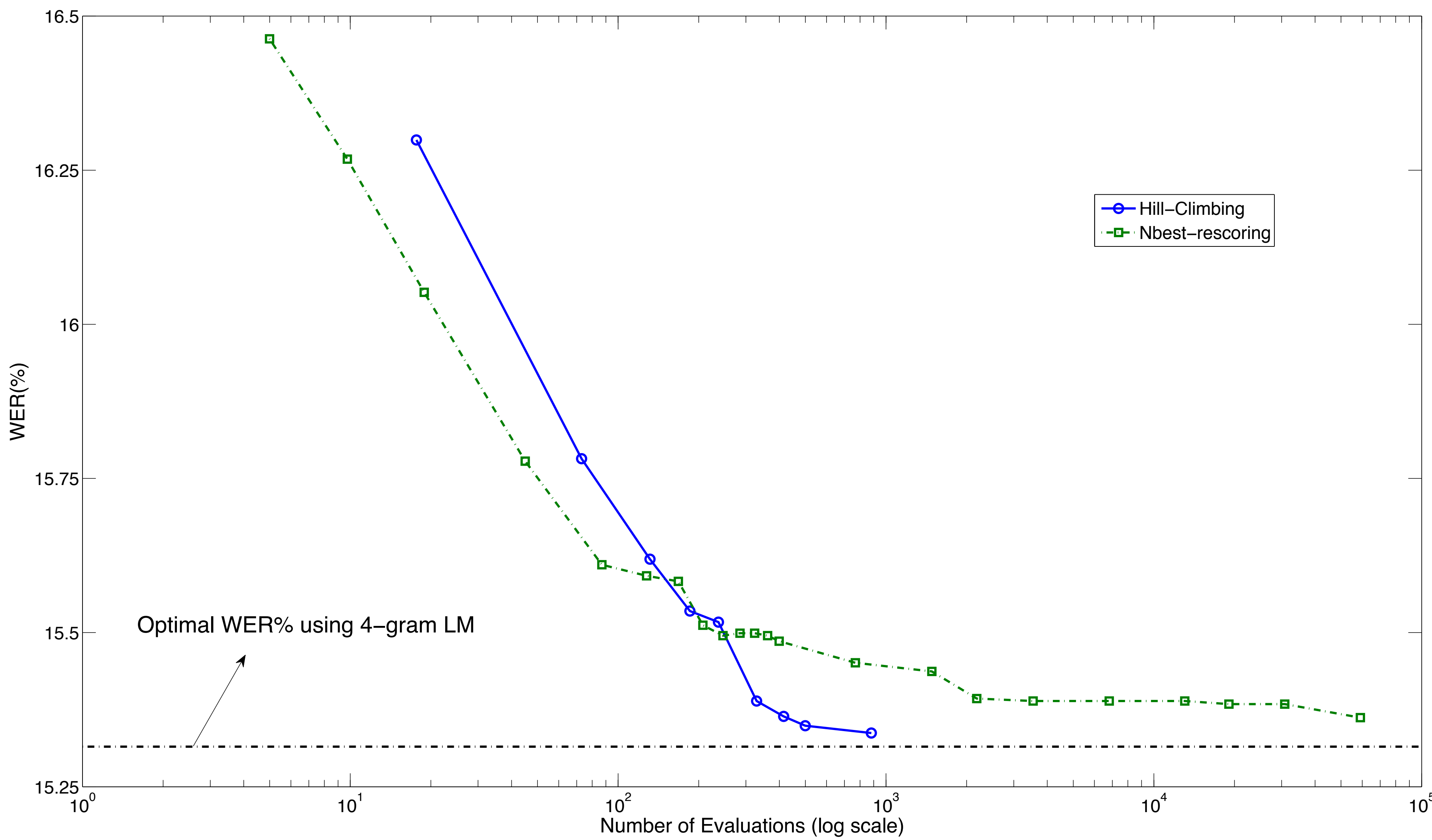
Results

Model *M* LM on rt04



Results

4-gram LM on dev04f



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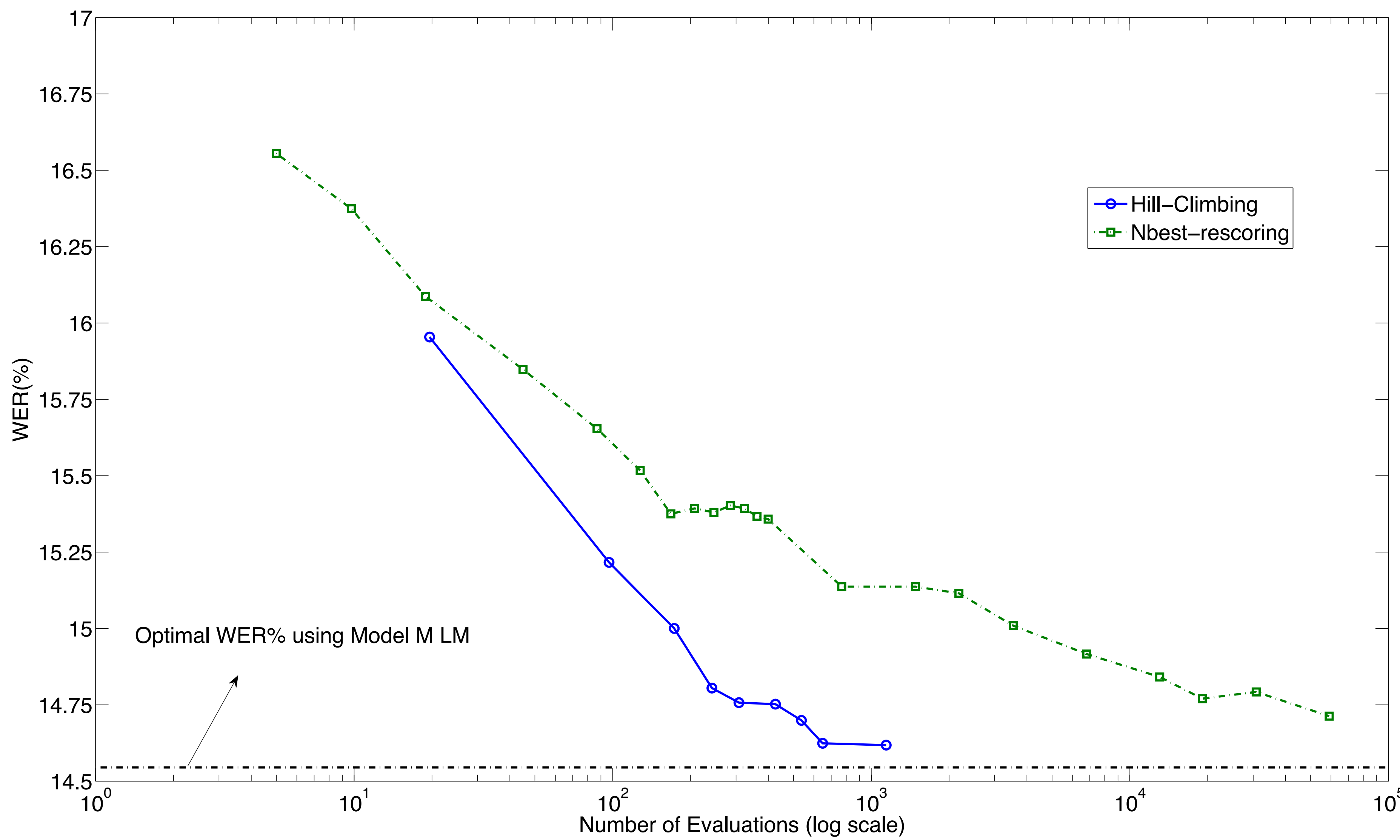

Discussion

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At each step the moves are selected (from neighborhood set) based on their ***quality under the new model*** (in contrast to *N*-best rescoring where the evaluating points are selected based on the initial model)

2 The problem with *N*-best rescoring (non-efficiency in terms of effective evaluations) is more severe when the ***rescoring model is different/orthogonal*** to the initial model

Questions?

Thank you!