Sparse Feature Learning

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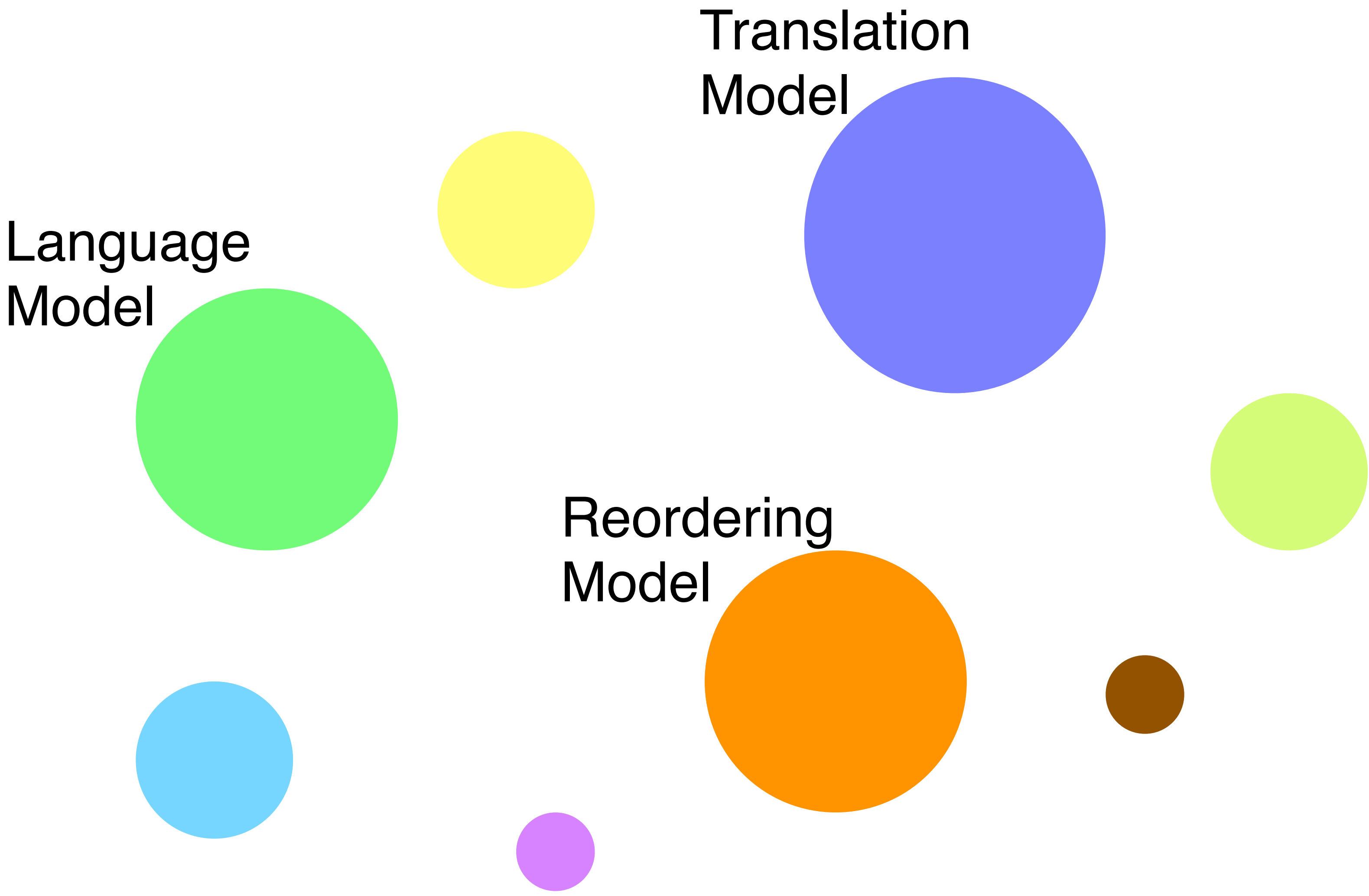
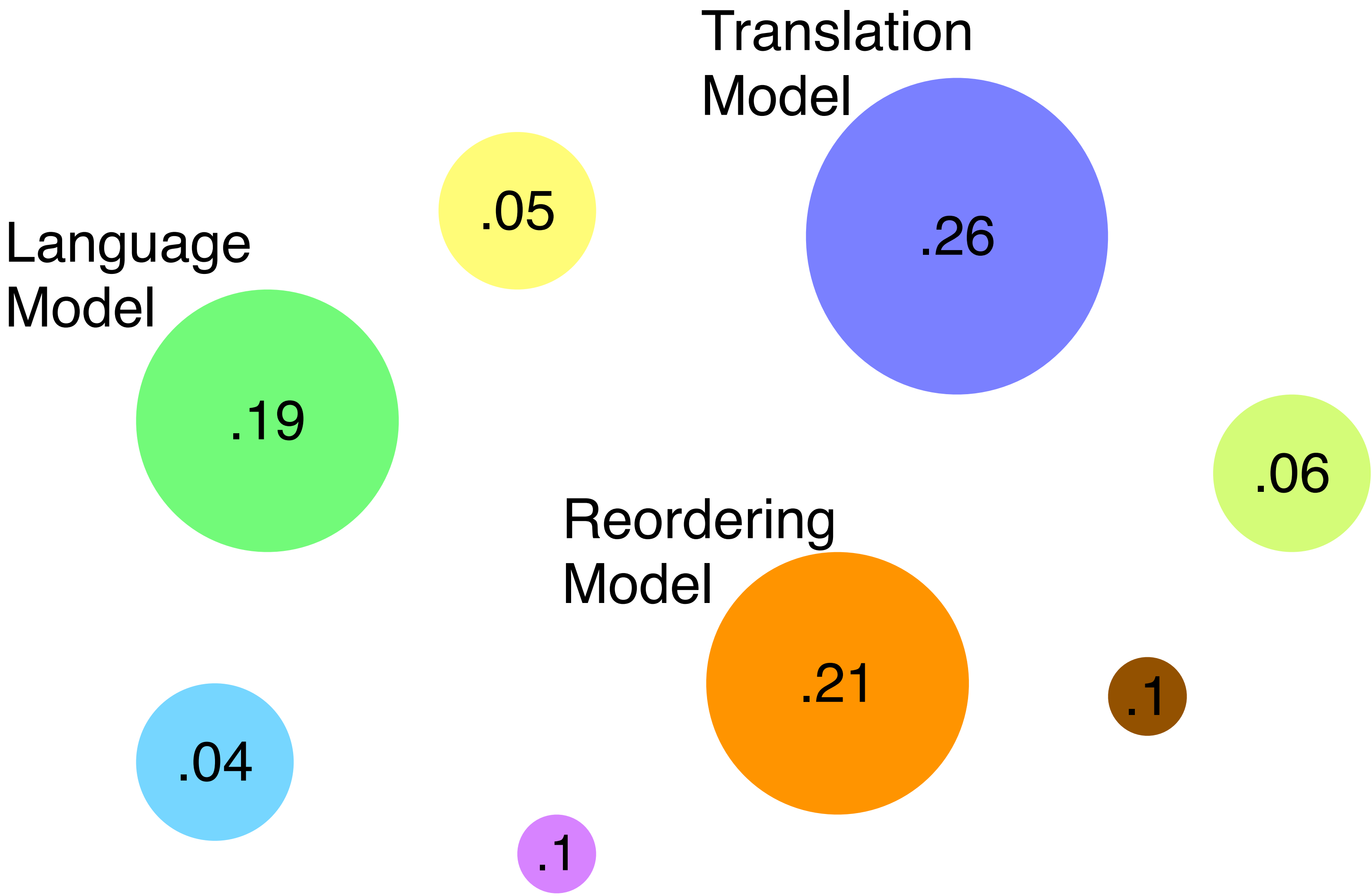
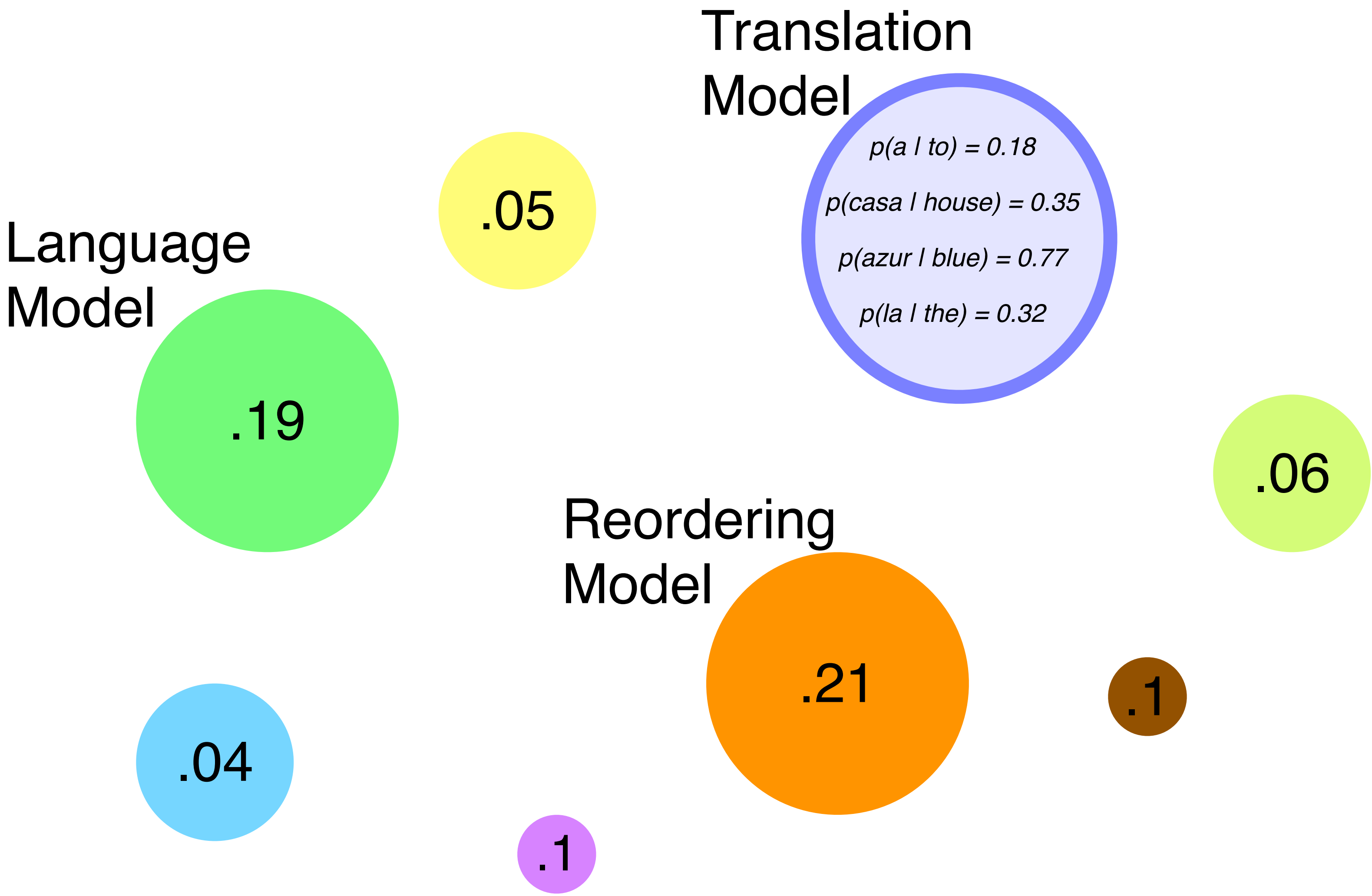
Multiple Component Models



Component Weights



Even More Numbers Inside

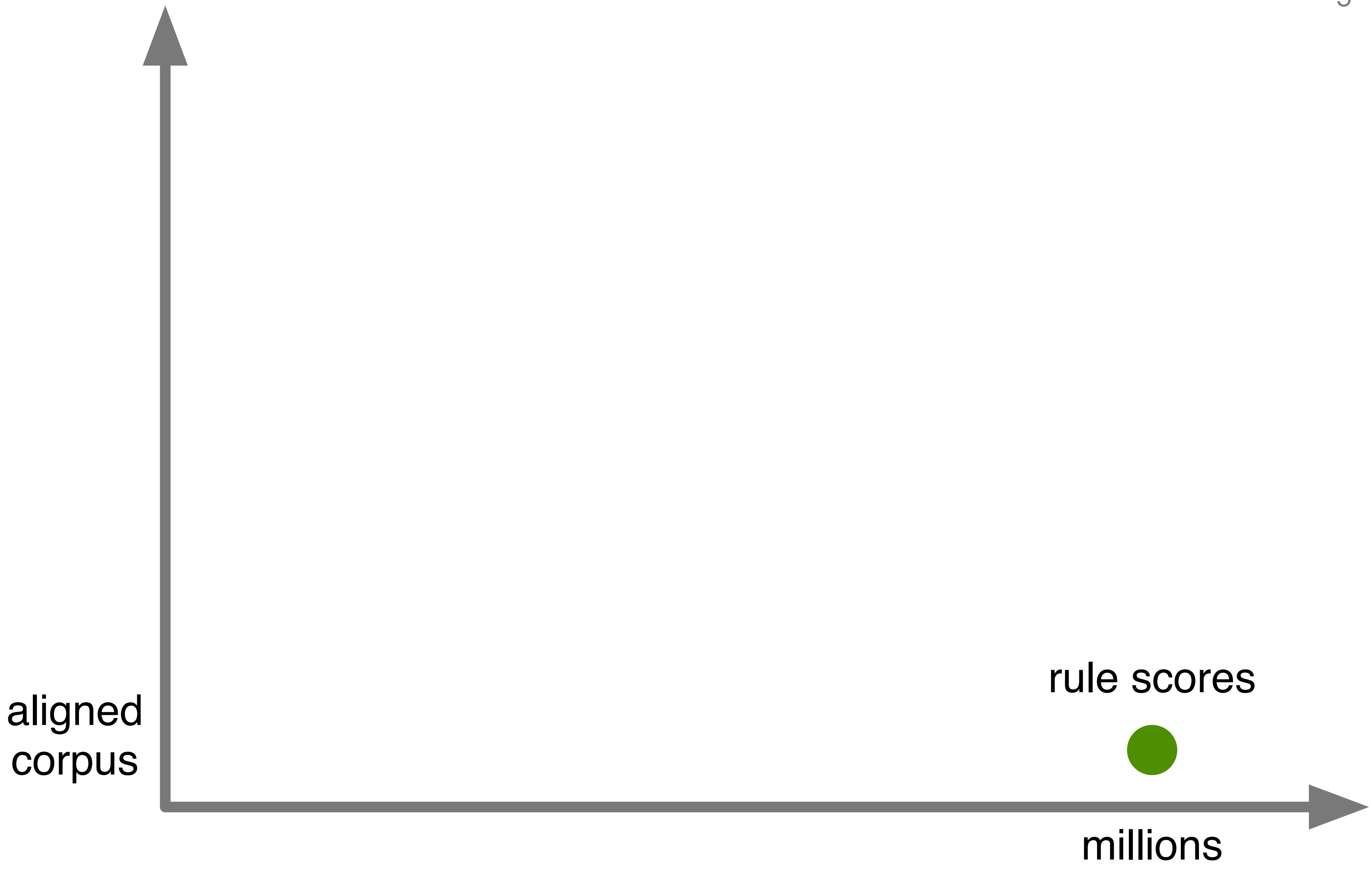


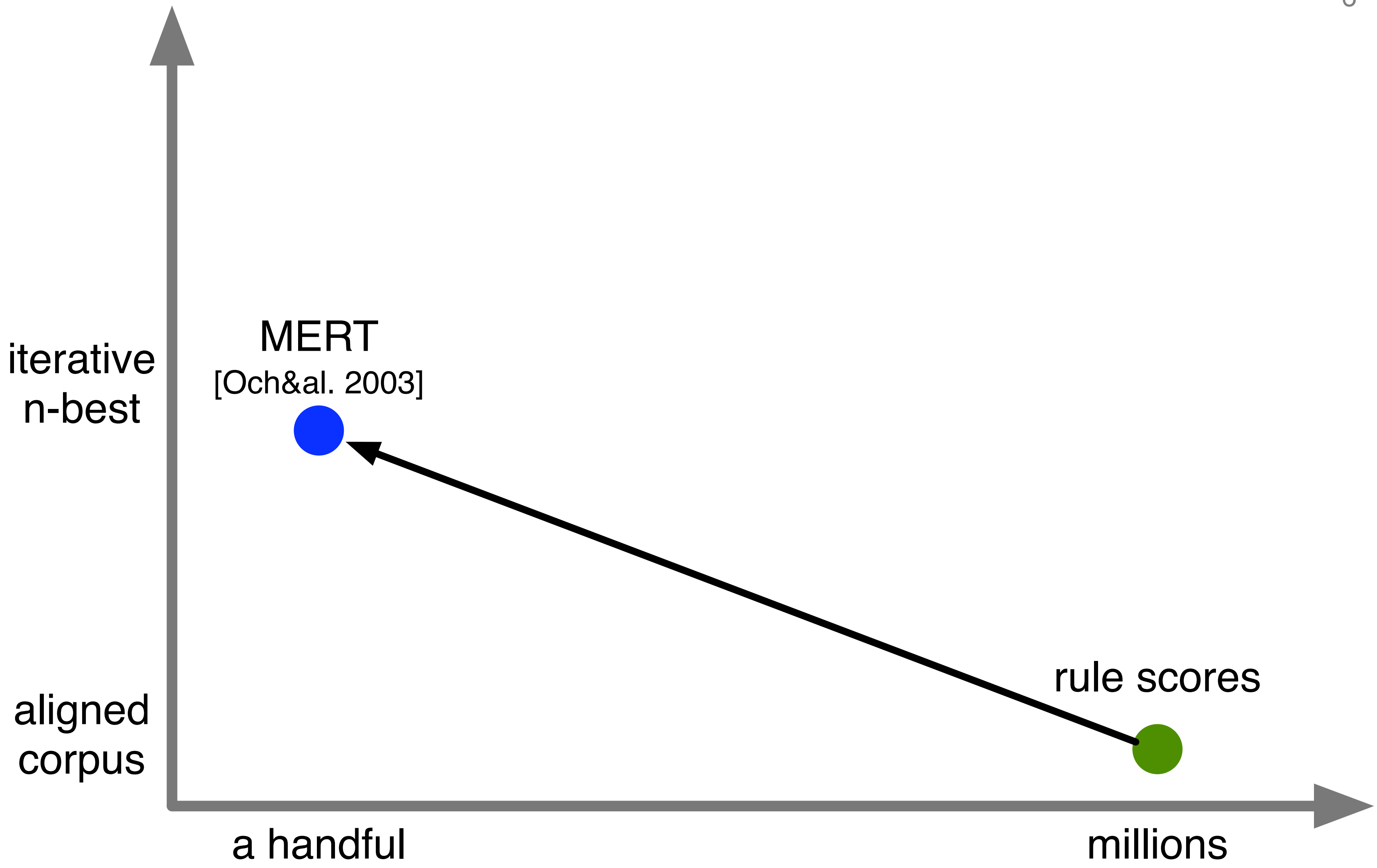
Grand Vision

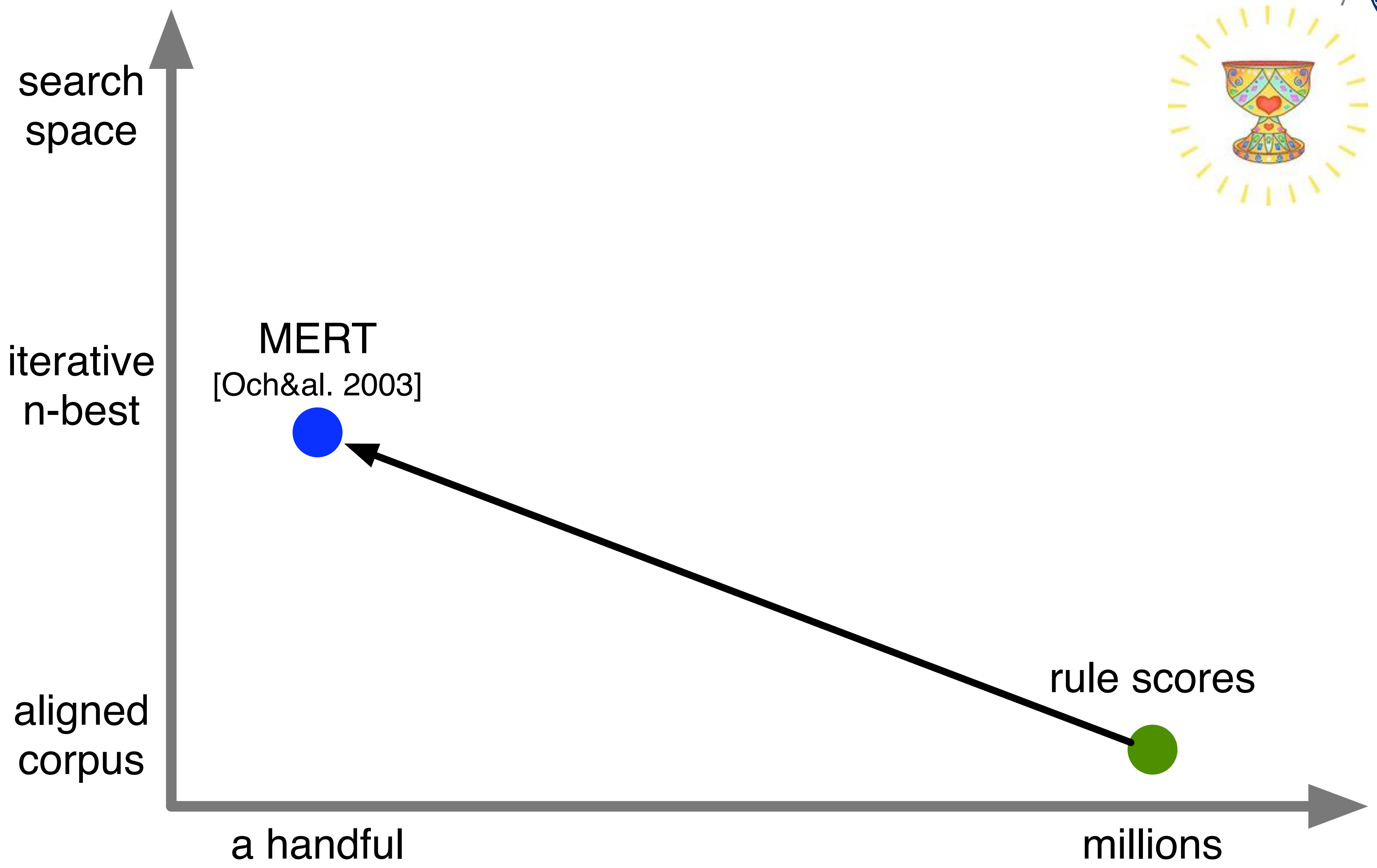
- There are millions of parameters
  - each phrase translation score
  - each language model n-gram
  - etc.

- Can we train them all discriminatively?

- This implies optimization over the entire training corpus


aligned
corpus
rule scores
millions


iterative
n-best
aligned
corpus
MERT
[Och&al. 2003]
rule scores
a handful
millions


search
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iterative
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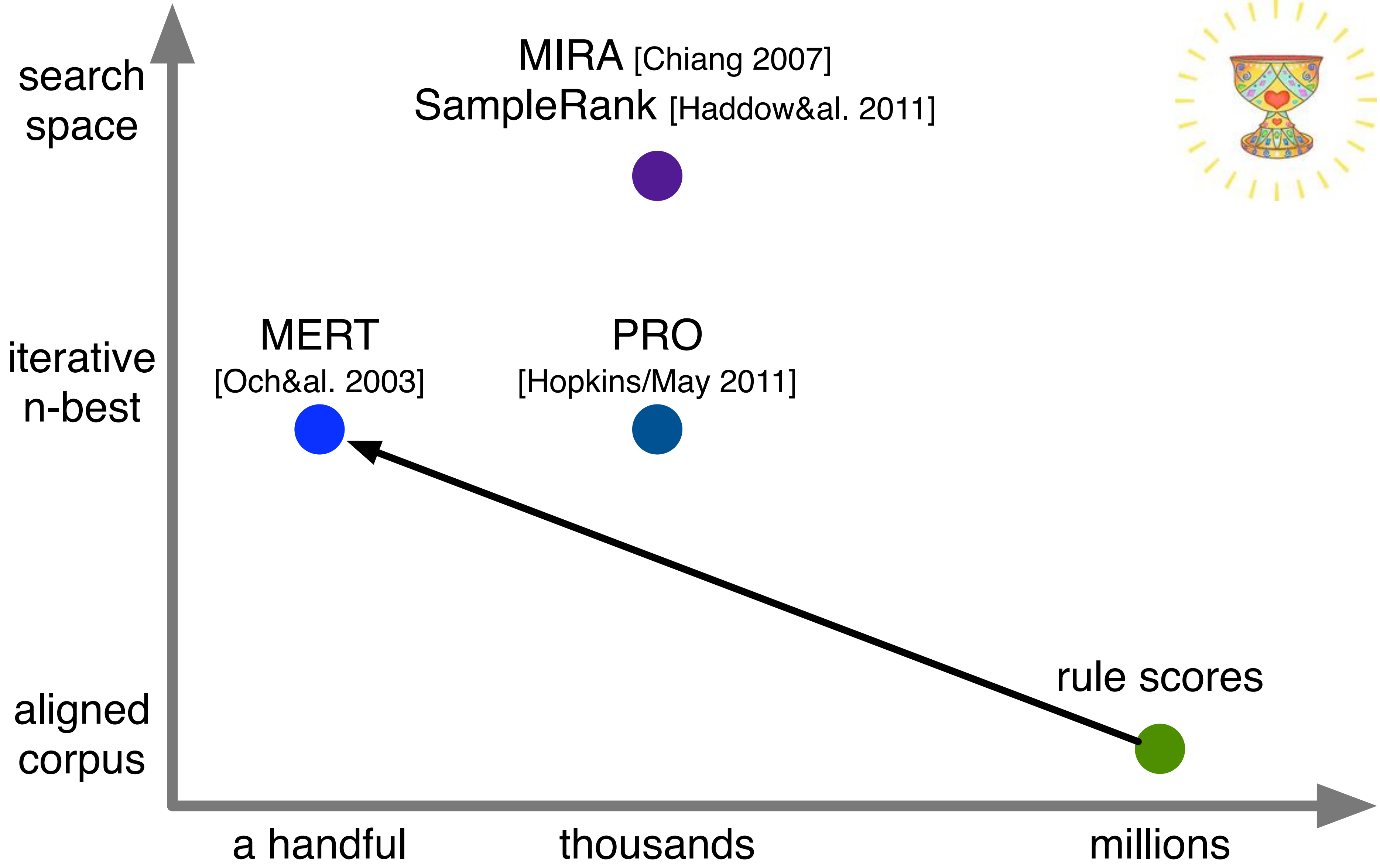
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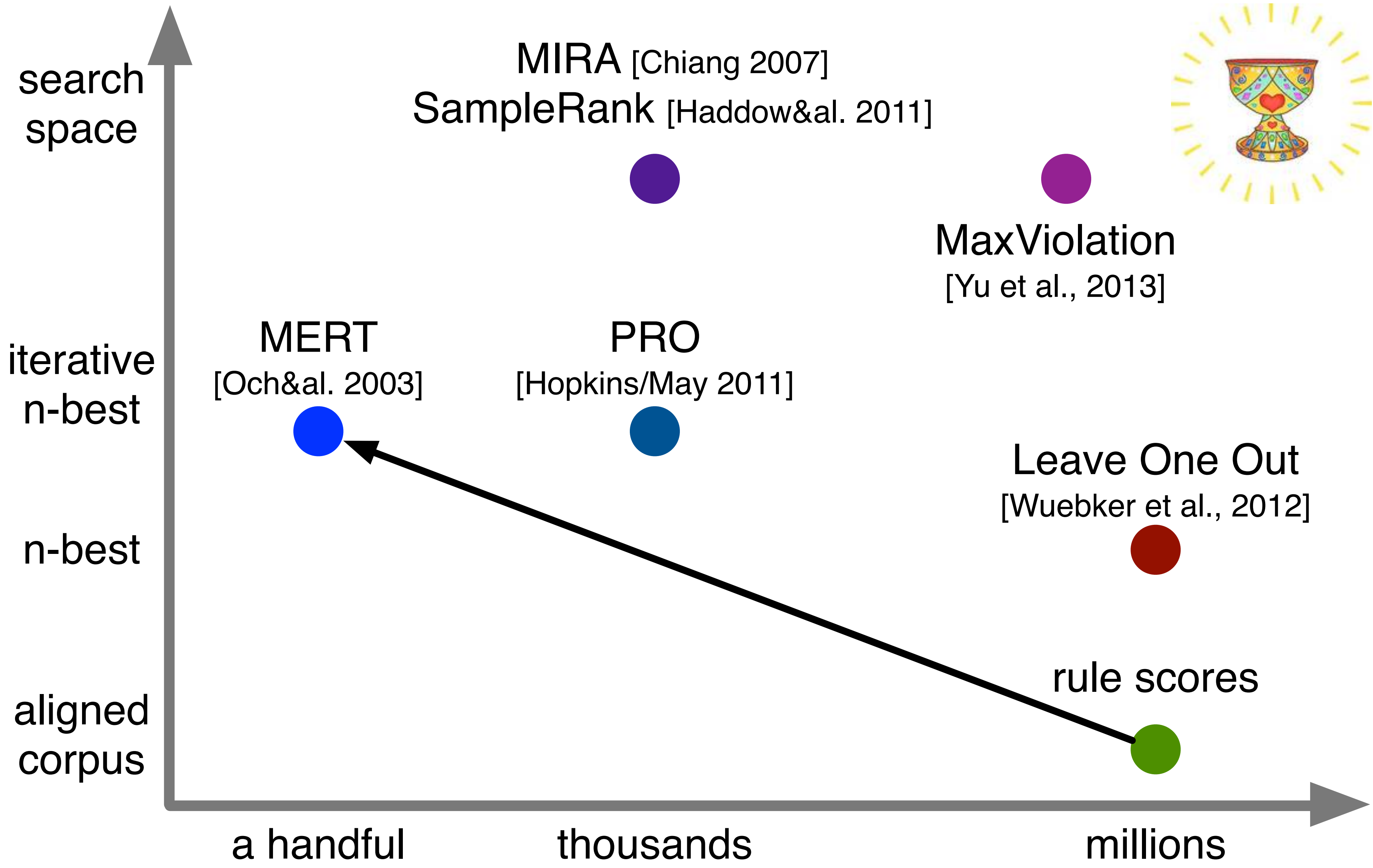
search space
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MIRA [Chiang 2007]
SampleRank [Haddow&al. 2011]
MaxViolation
[Yu et al., 2013]
MERT
[Och&al. 2003]
PRO
[Hopkins/May 2011]
Leave One Out
[Wuebker et al., 2012]
rule scores

Strategy and Core Problems

- Process each sentence pair in the training corpus
- Optimize parameters towards producing the reference translation
- Reference translation may not be producible by model
  - optimize towards most similar translation
  - or, only process sentence pair partially
- Avoid overfitting
- Large corpora require efficient learning methods

Sentence Level vs. Corpus Level Error Metric

- Optimizing BLEU requires optimizing over the entire training corpus

$$\text{BLEU}(\{\mathbf{e}_i^{\text{best}} = \text{argmax}_{\mathbf{e}_i} \sum_j h_j(\mathbf{e}_i, \mathbf{f}_i)\ \lambda_i\}, \{\mathbf{e}_i^{\text{ref}}\})$$

- Life would be easier, if we could sum over sentence level scores

$$\sum_i \text{BLEU}'(\ \text{argmax}_{\mathbf{e}_i} \sum_j (h_j(\mathbf{e}_i, \mathbf{f}_i)\ \lambda_i),\ \mathbf{e}_i^{\text{ref}}\ )$$

- For instance, BLEU+1

features

Core Rule Properties

- Frequency of phrase (binned)
- Length of phrase
  - number of source words
  - number of target words
  - number of source and target words
- Unaligned / added (content) words in phrase pair
- Reordering within phrase pair

Lexical Translation Features

- $\text{lex}(e)$ fires when an output word e is generated
- $\text{lex}(f, e)$ fires when an output word e is generated aligned to a input word f
- $\text{lex}(\text{NULL}, e)$ fires when an output word e is generated unaligned
- $\text{lex}(f, \text{NULL})$ fires when an input word e is dropped
- Could also be defined on part of speech tags or word classes

Lexicalized Reordering Features

- Replacement of lexicalized reordering model

- Features differ by
  - lexicalized by first or last word of phrase (source or target)
  - word representation replaced by word class
  - orientation type

Domain Features

- Indicator feature that the rule occurs in one specific domain
- Probability that the rule belongs to one specific domain
- Domain-specific lexical translation probabilities

Syntax Features

- If we have syntactic parse trees, many more features
  - number of nodes of a particular kind
  - matching of source and target constituents
  - reordering within syntactic constituents
- Parse trees are a by-product of syntax-based models
- More on that in future lectures

Every Number in Model

- Phrase pair indicator feature
- Target n-gram feature
- Phrase pair orientation feature

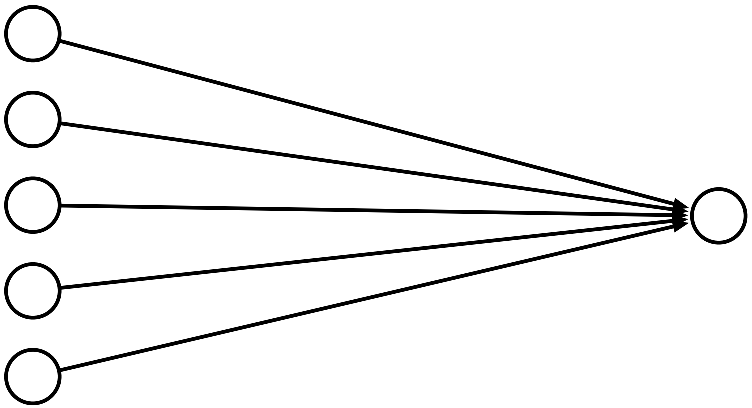
perceptron algorithm

Optimizing Linear Model

- We consider each sentence pair $(\mathbf{e}_i, \mathbf{f}_i)$ and its alignment $\mathbf{a}_i$
- To simplify notation, we define derivation $\mathbf{d}_i = (\mathbf{e}_i, \mathbf{f}_i, \mathbf{a}_i)$
- Model score is weighted linear combination of feature values h_j and weights λ_j

$$\text{score}(\lambda, \mathbf{d}_i) = \sum_j \lambda_j \, h_j(\mathbf{d}_i)$$

- Such models are also known as single layer perceptrons



Reference and Model Best

- Besides the reference derivation $\mathbf{d}_i^{\text{ref}}$ for sentence pair i and its score

$$\text{score}(\lambda, \mathbf{d}_i^{\text{ref}}) = \sum_j \lambda_j \, h_j(\mathbf{d}_i^{\text{ref}})$$

- We also have the model best translation

$$\mathbf{d}_i^{\text{best}} = \text{argmax}_{\mathbf{d}} \, \text{score}(\lambda_i, \mathbf{d}_i) = \text{argmax}_{\mathbf{d}} \sum_j \lambda_j \, h_j(\mathbf{d}_i)$$

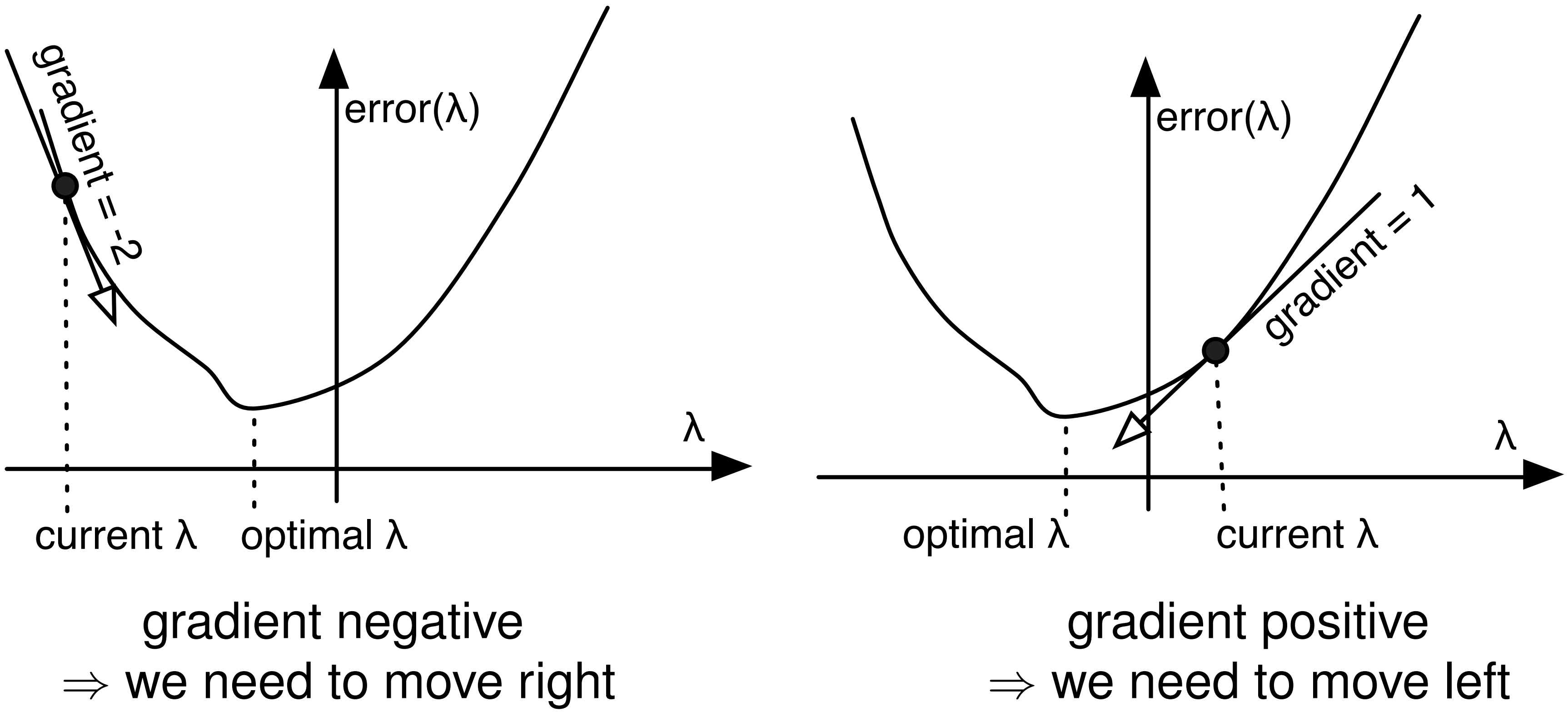
- ... and its model score

$$\text{score}(\lambda, \mathbf{d}_i^{\text{best}}) = \sum_j \lambda_j \, h_j(\mathbf{d}_i^{\text{best}})$$

- We can view the error in our model as a function of its parameters λ

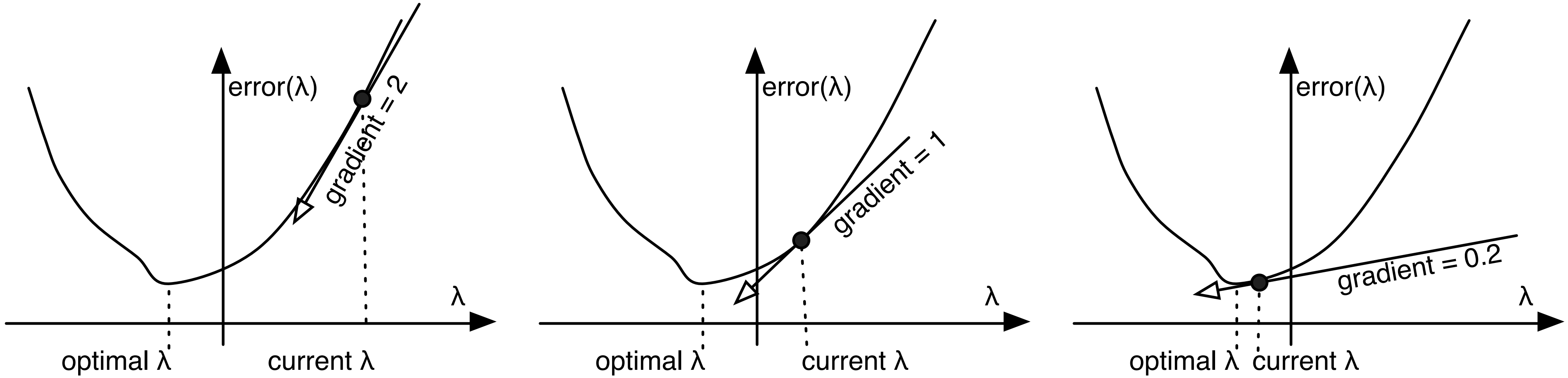
$$\text{error}(\lambda, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}}) = \text{score}(\lambda, \mathbf{d}_i^{\text{best}}) - \text{score}(\lambda, \mathbf{d}_i^{\text{ref}})$$

Follow the Direction of Gradient



- Assume that we can compute the gradient $\frac{d}{d\lambda}\text{error}(\lambda)$ at any point
- If the error curve is convex, gradient points in the direction the optimum

Move Relative to Steepness



gradient high (steep)
⇒ move a lot

gradient medium
⇒ move some

gradient low (flat)
⇒ move little

- If the error curve is convex, size of gradient indicates speed of change
- Model update $\Delta\lambda = -\frac{d}{d\lambda}\text{error}(\lambda)$

Stochastic Gradient Descent

- We want to minimize the error

$$\text{error}(\lambda, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}}) = \text{score}(\lambda, \mathbf{d}_i^{\text{best}}) - \text{score}(\lambda, \mathbf{d}_i^{\text{ref}})$$

- In stochastic gradient descent, we follow direction of gradient

$$\frac{d}{d\ \lambda}\,\text{error}(\lambda, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}})$$

- For each λ_j, we compute the gradient pointwise

$$\frac{d}{d\ \lambda_j}\,\text{error}(\lambda_j, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}}) = \frac{d}{d\ \lambda_j}\,\text{score}(\lambda, \mathbf{d}_i^{\text{best}}) - \text{score}(\lambda, \mathbf{d}_i^{\text{ref}})$$

Stochastic Gradient Descent

- Gradient with respect to λ_j

$$\frac{d}{d\,\lambda_j}\,\text{error}(\lambda_j, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}}) = \frac{d}{d\,\lambda_j}\,\sum_{j'} \lambda_{j'}\, h_{j'}(\mathbf{d}_i^{\text{best}}) - \sum_{j'} \lambda_{j'}\, h_{j'}(\mathbf{d}_i^{\text{ref}})$$

- For $\lambda'_j \neq \lambda_j$, the terms $\lambda_{j'}\, h_{j'}(\mathbf{d}_i)$ are constant, so they disappear

$$\frac{d}{d\,\lambda_j}\,\text{error}(\lambda_j, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}}) = \frac{d}{d\,\lambda_j}\,\lambda_j\, h_j(\mathbf{d}_i^{\text{best}}) - \lambda_j\, h_j(\mathbf{d}_i^{\text{ref}})$$

- The derivative of a linear function is its factor

$$\frac{d}{d\,\lambda_j}\,\text{error}(\lambda_j, \mathbf{d}_i^{\text{best}}, \mathbf{d}_i^{\text{ref}}) = h_j(\mathbf{d}_i^{\text{best}}) - h_j(\mathbf{d}_i^{\text{ref}})$$

$\Rightarrow$ Our model update is $\lambda_j^{\text{new}} = \lambda_j - (h_j(\mathbf{d}_i^{\text{best}}) - h_j(\mathbf{d}_i^{\text{ref}}))$

Intuition

- Feature values in model best translation
- Feature values in reference translation
- Intuition:
  - promote features whose value is bigger in reference
  - demote features whose value is bigger in model best

Algorithm

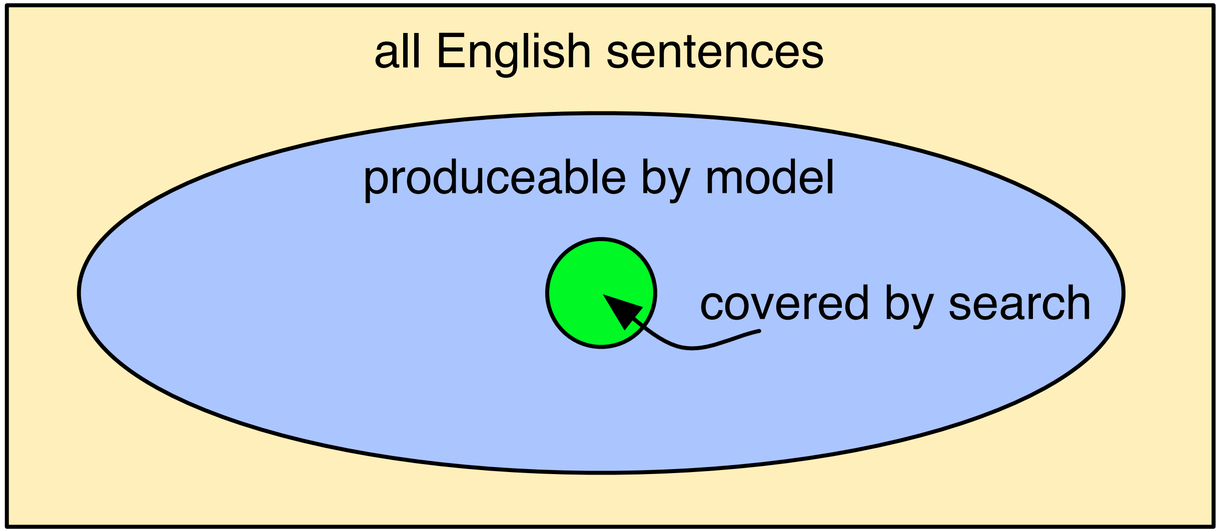
Input: set of sentence pairs (**e**,**f**), set of features
Output: set of weights λ for each feature

```
λ_i = 0 for all i
while not converged do
    for all foreign sentences f do
        d_best = best derivation according to model
        d_ref = reference derivation
        if d_best ≠ d_ref then
            for all features h_i do
                λ_i += h_i(d_ref) − h_i(d_best)
            end for
        end if
    end for
end while
```

generating the reference

Failure to Generate Reference

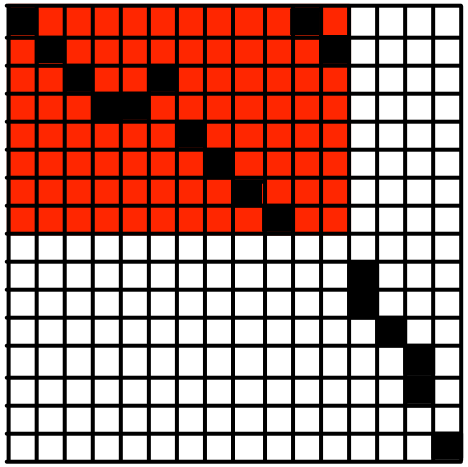
- Reference translation may be anywhere in this box



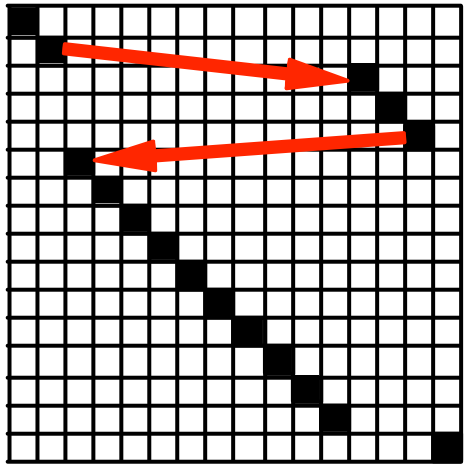
- If produceable by model → we can compute feature scores
- If not → we can not

Causes

- Reference translation in tuning set not literal
- Failure even if phrase pairs are extracted from same sentence pair
- Examples



alignment points too distant
→ phrase pair too big to extract



required reordering distance too large
→ exceeds distortion limit of decoder

Sentence Level BLEU

- BLEU+1
  - add one free n-gram count to statistics $\rightarrow$ avoids BLEU score of 0
  - however: wrong balance between 1-4 grams, too drastic brevity penalty
- BLEU impact
  - leave all other sentence translations fixed
  - collect n-gram matches and totals from them
  - add n-gram matches and total from current candidate

  $\rightarrow$ consider impact on overall BLEU score
- Incremental BLEU impact
  - maintain decaying statistics for n-gram matches, total n-grams

$$\text{count}_t = \frac{9}{10}\,\text{count}_{t-1} + \text{current-count}_t$$

Problems with Max-BLEU Training

- Consider the following Arabic sentence (written left-to-right in Buckwalter romanization) with English glosses:

sd	qTEp	mn	AlkEk	AlmmlH	”	brytzl	”	Hlqh	.
blocked	piece	of	biscuit	salted	”	pretzel	”	his-throat	

- Very literal translation might be

A piece of a salted biscuit, a ”pretzel,” blocked his throat.

- But reference translation is

A pretzel, a salted biscuit, became lodged in his throat.

- Reference accurate, but major transformations

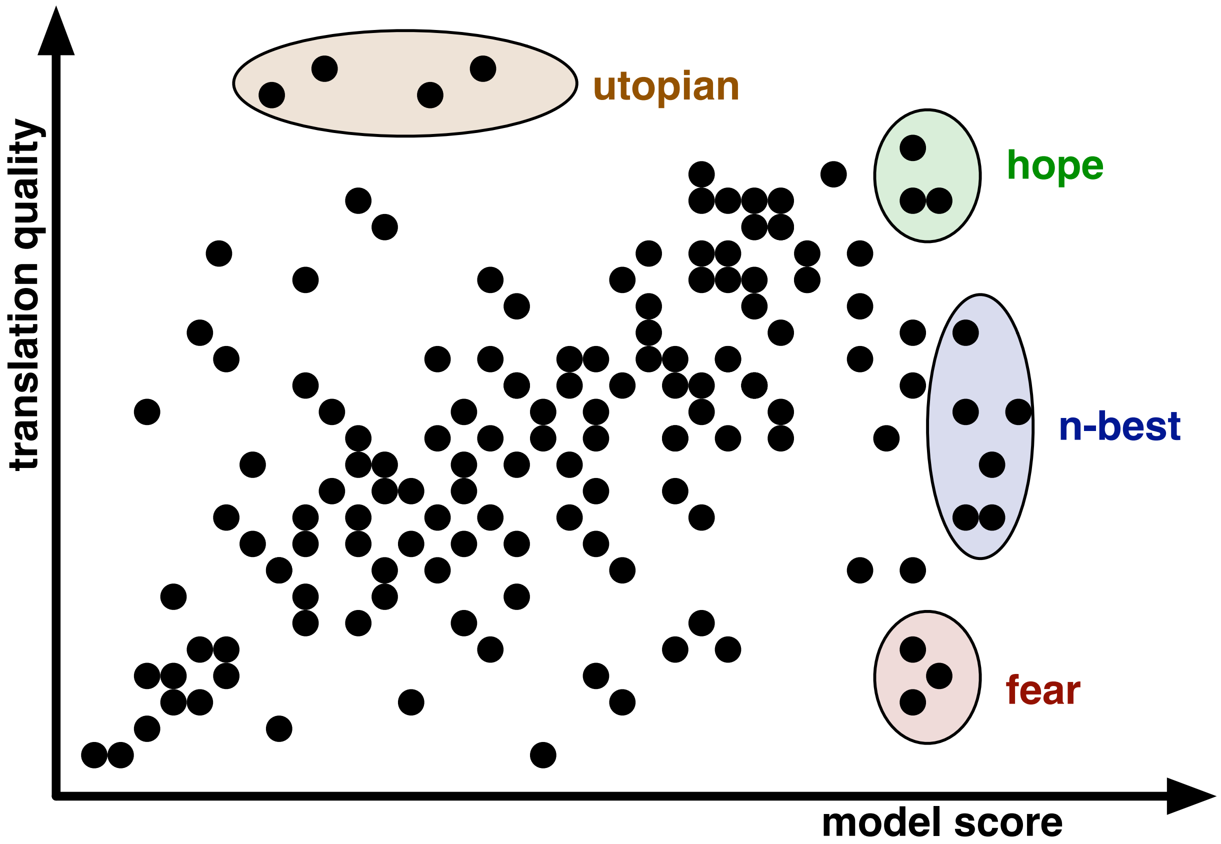
- Trying to approximate reference translation may lead to bad rules

note: example from Chiang (2012)

mira

Hope and Fear

- Bad: optimize towards utopian, away from n-best
- Good: optimize towards hope, away from fear



Hope and Fear Translations

- Hope translation

$$\mathbf{d}^{\text{hope}} = \text{argmax}_{\mathbf{d}}\ \mathsf{BLEU}(\mathbf{d}) + \text{score}(\mathbf{d})$$

- Finding the fear translation
  - Metric difference (should be big)

$$\Delta\mathsf{BLEU}(\mathbf{d}^{\text{hope}}, \mathbf{d}) = \mathsf{BLEU}(\mathbf{d}^{\text{hope}}) - \mathsf{BLEU}(\mathbf{d})$$

  - Score difference (should be small or negative)

$$\Delta\text{score}(\lambda, \mathbf{d}^{\text{hope}}, \mathbf{d}) = \text{score}(\lambda, \mathbf{d}^{\text{hope}}) - \text{score}(\lambda, \mathbf{d})$$

  - Margin

$$v(\lambda, \mathbf{d}^{\text{hope}}, \mathbf{d}) = \Delta\text{BLEU}(\mathbf{d}^{\text{hope}}, \mathbf{d}) - \Delta\text{score}(\lambda, \mathbf{d}^{\text{hope}}, \mathbf{d})$$

  - Fear translation $\mathbf{d}^{\text{fear}} = \text{argmax}_{\mathbf{d}}\ v(\lambda, \mathbf{d}^{\text{hope}}, \mathbf{d})$

Margin Infused Relaxed Algorithm (MIRA)

- Stochastic gradient descent update with learning weight δ_i

$$\lambda_j^{\text{new}} = \lambda_j - \delta_i \left(h_j(\mathbf{d}_i^{\text{fear}}) - h_j(\mathbf{d}_i^{\text{hope}}) \right)$$

- Updates should depend on margin

$$\delta_i = \min \left(C, \frac{\Delta\text{BLEU}(\mathbf{d}_i^{\text{hope}}, \mathbf{d}_i^{\text{fear}}) - \Delta\text{score}(\mathbf{d}_i^{\text{hope}}, \mathbf{d}_i^{\text{fear}})}{||\Delta h||^2} \right)$$

- The math behind this is a bit complicated

Different Learning Rates for Features

- For some features, we have a lot of evidence (coarse features)
- Others occur only rarely (sparse features)
- After a while, we do not want to change coarse features too much

⇒ Adaptive Regularization of Weights (AROW)

  - record confidence in weights over time
  - include this in the learning rate for each feature

Parallelization

- Training is computationally expensive

⇒ Break up training data into batches

- After processing all the batches, average the weights

- Not only a speed-up, also seems to improve quality

- Allows parallel processing, but requires inter-process communication

Sample Rank

- Generating hope and fear translations is expensive
- Sample good/bad by random walk through alignment space
  - use operations as in Gibbs samples
  - vary one translation option choice
  - vary one reordering decision
  - vary one phrase segmentation decision
  - adopt new translation based on relative score
- Compare current translation against its neighbors

$\rightarrow$ apply MIRA update if more costly translation has higher BLEU

Batch MIRA

- MIRA requires translation of each sentence on demand
  - repeated decoding needed
  - computationally very expensive

- Batch MIRA
  - n-best list or search graph (lattice)
  - straightforward parallelization
  - does not seem to harm performance

pro

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%

- Higher quality translation (BLEU+1) should rank higher

Pick 2 Translations at Random

- 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%**

- Higher quality translation (BLEU+1) should rank higher

One is Better than the Other

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

Translation	Feature values						BLEU+1
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he is not for home	-36.70	-13.52	-17.09	-6.22	-7.82	-5	**32.5%**

- Higher quality translation (BLEU+1) should rank higher

Learn from the Pairwise Sample

- Pairwise sample
  - $\overrightarrow{\textbf{bad}} = (-31.75, -17.25, -20.43, -4.90, -6.90, -5)$
  - $\overrightarrow{\textbf{good}} = (-36.70, -13.52, -17.09, -6.22, -7.82, -5)$

- Learn a classifier
  - $\overrightarrow{\textbf{bad}} - \overrightarrow{\textbf{good}} \rightarrow$ ☹
  - $\overrightarrow{\textbf{good}} - \overrightarrow{\textbf{bad}} \rightarrow$ ☺

- Use off the shelf maximum entropy classifier to learn weights for each feature e.g., MegaM (http://www.umiacs.umd.edu/∼hal/megam/)

Sampling

- Collect samples for each sentence pair in tuning set

- For each sentence, sample 1000-best list for 50 pairwise samples

- Reject samples if difference in BLEU+1 score is too small (≤ 0.05)

- Iterate process
  1. set default weights
  2. generate n-best list
  3. build classifier
  4. adopt classifier weights
  5. go to 2, unless converged

leave one out

Leave One Out Training

- Train initial baseline model
- Force translate the training data:
  require decoder to match the reference translation
- Collect statistics over translation rules used
- Leave one out:
  do not use translation rules originally collected from current sentence pair
- Related to jackknife
  - 90% of training data used for rule collection
  - 10% to validate rules
  - rotate

Translate Almost All Sentences

- Relaxed leave-one-out
  - allow rules originally collected from current sentence pair
  - very costly $\rightarrow$ only used, if everything else fails

- Allow single word translations (avoid OOV)

- Larger distortion limit

- Word deletion and insertion (very costly)

Model Re-Estimation

- Generate 100-best list
- Collect fractional counts from derivations

⇒ Much smaller model

⇒ Sometimes better model

max-violation perceptron

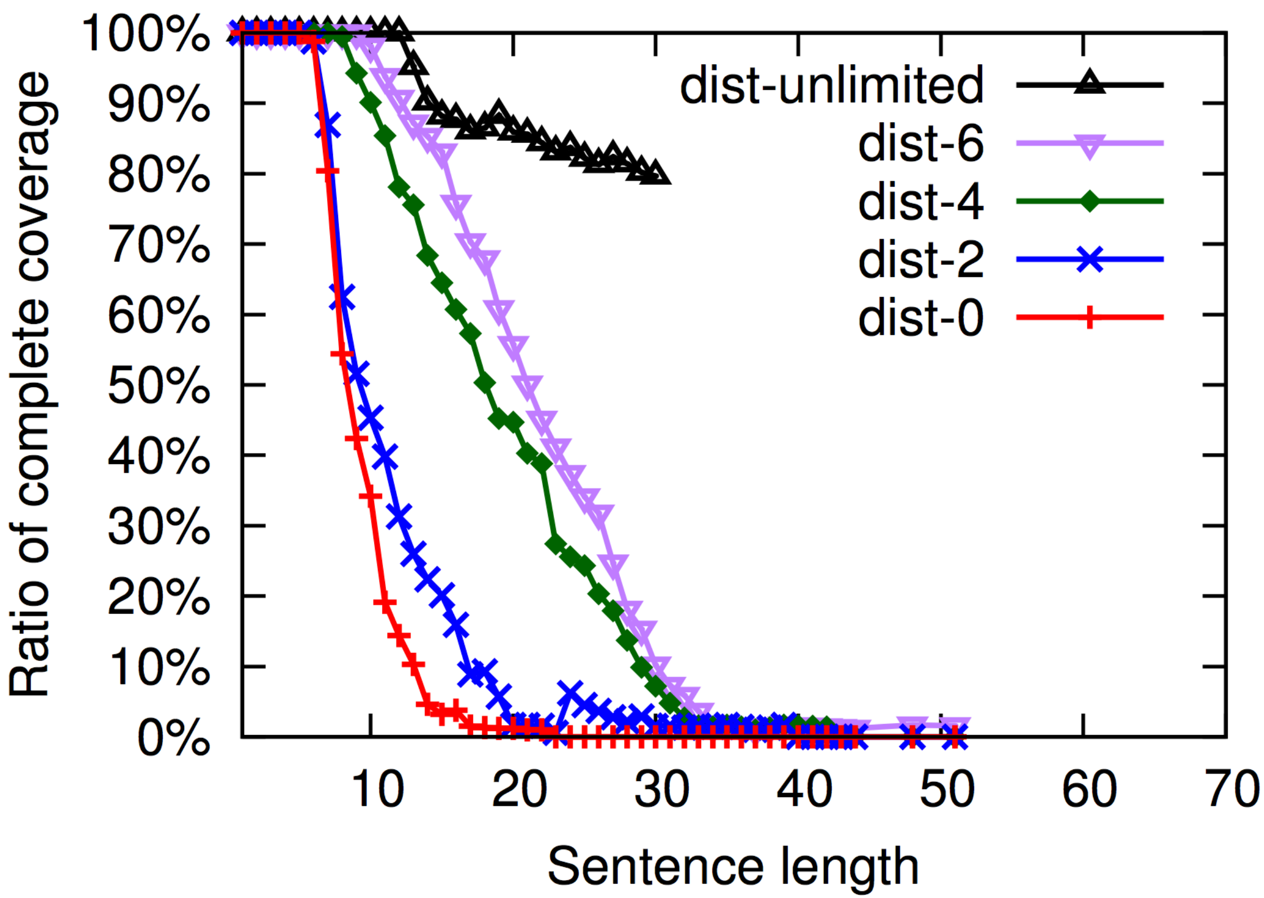
and

forced decoding

Perceptron over Full Training Corpus

- Early work on stochastic gradient descent over full training corpus unsuccessful
- One reason: Search errors break theoretical properties of convergence
- Are unreachable reference translations a problem?
  - yes: ignoring them leaves out large amounts of training data
  - no: data selection, non-literal translations are lower quality
- Idea: update when partial reference derivation falls out of beam

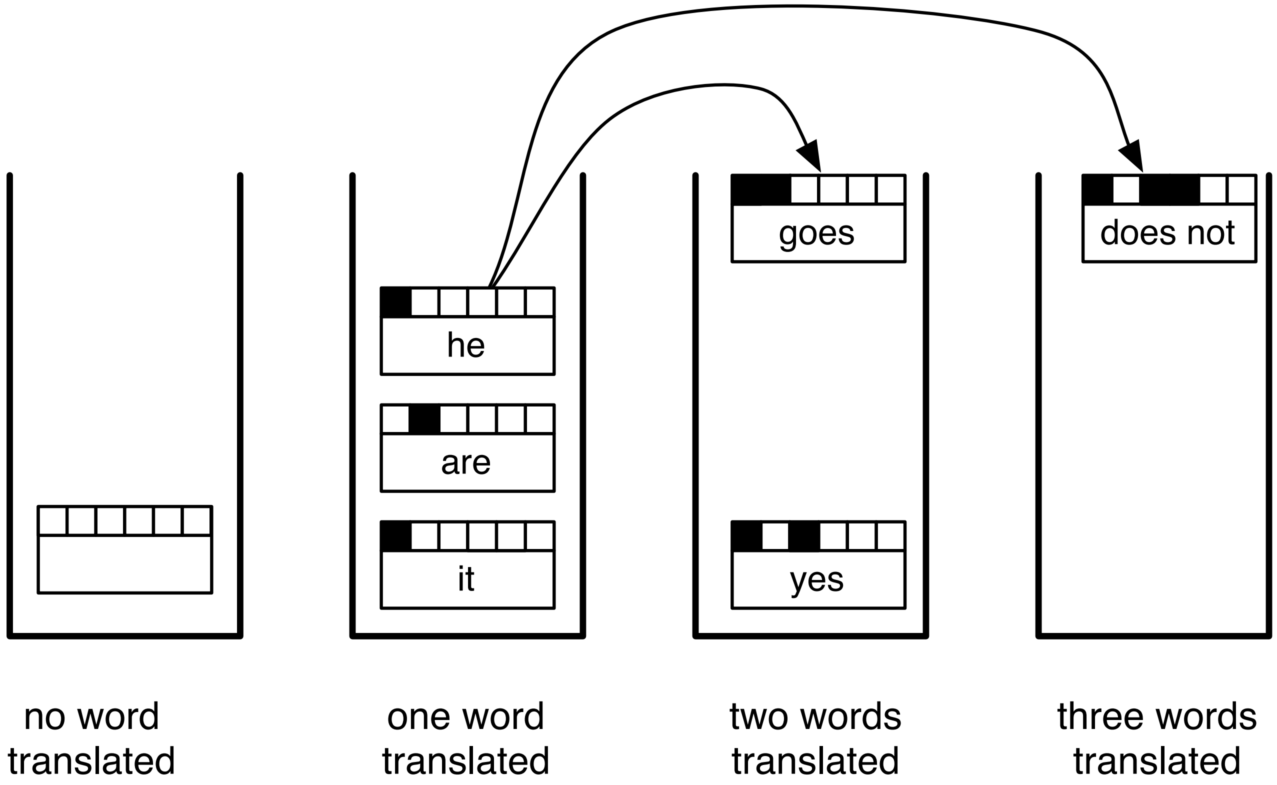
Reachability



Reachabillity by distortion limit and sentence length

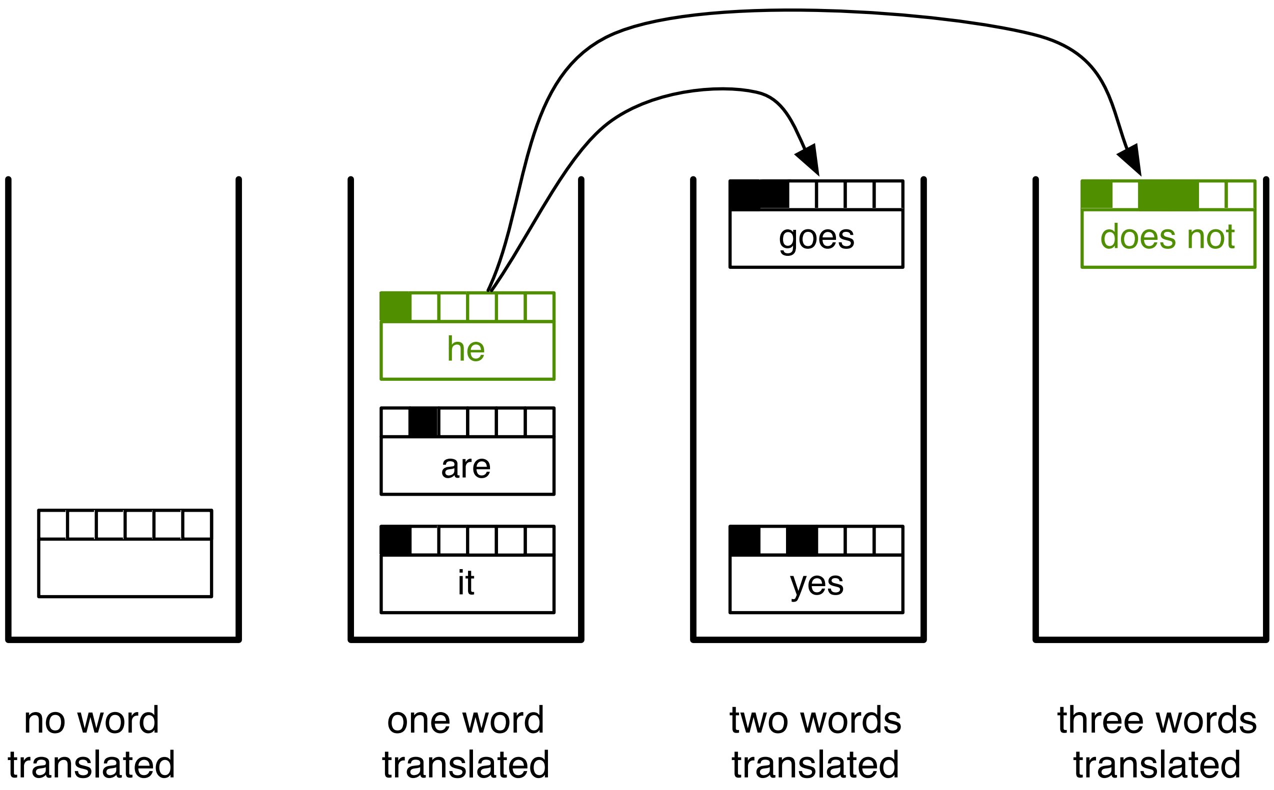
Chinese–English NIST [Yu et al., 2013]

Recall: Decoding



- Extend partial translations (=hypotheses) by adding translation options
- Organize hypotheses in stacks, prune out bad ones

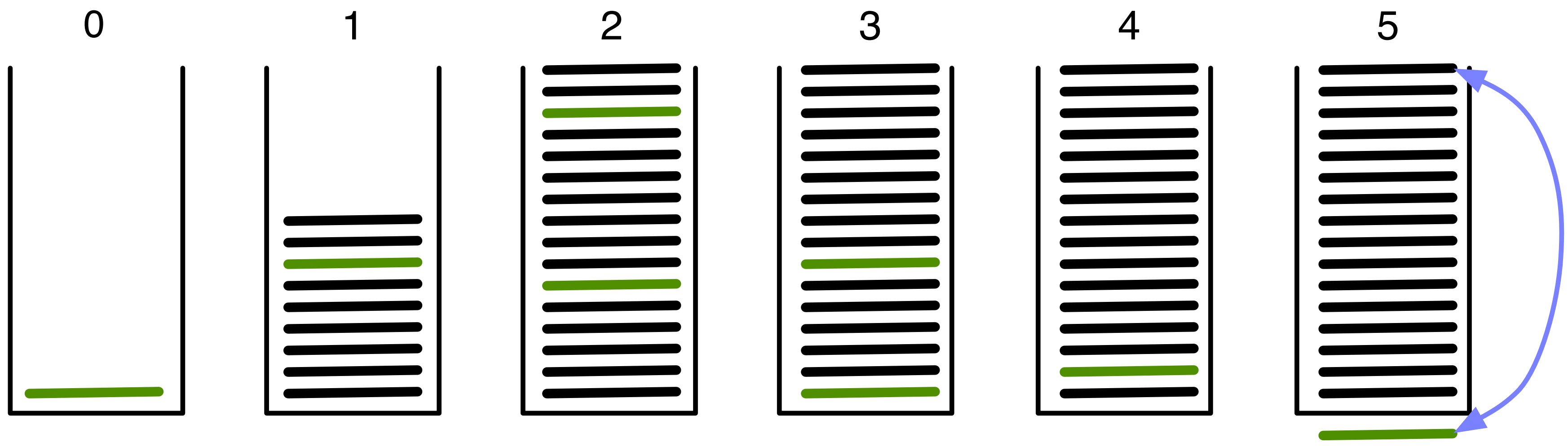
Matching the Reference



- Some hypotheses match the reference translation

he does not go home

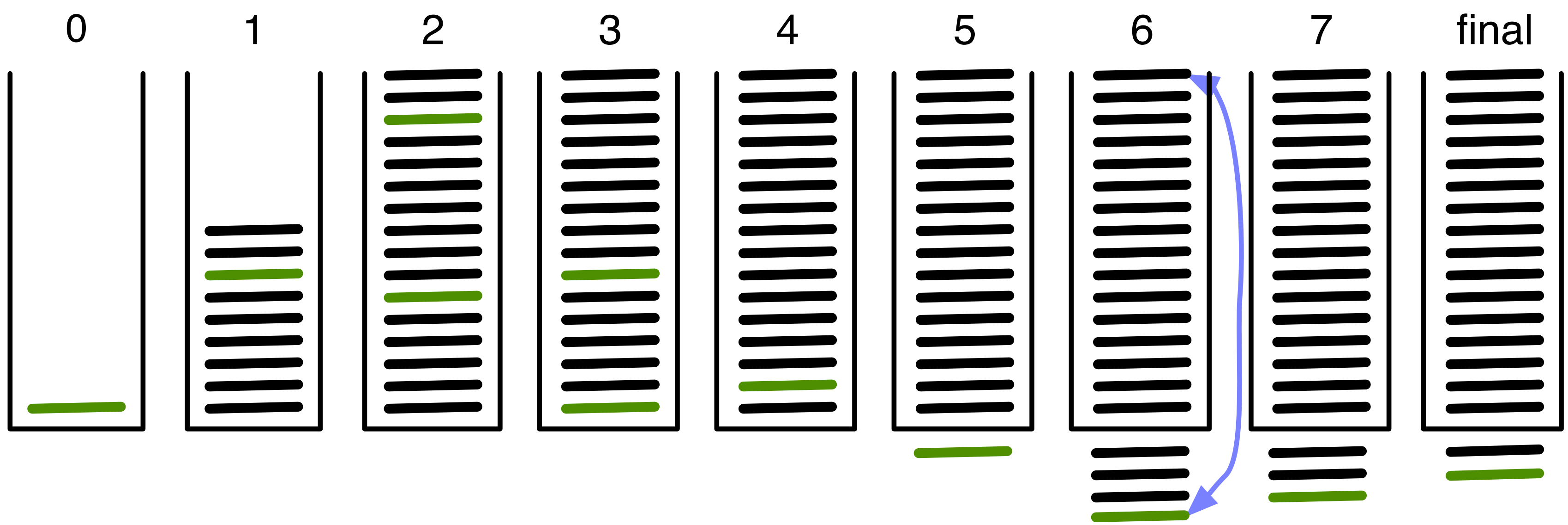
Early Updating



- At some point the best reference derivation may fall outside the beam
- Early updating
  - perceptron update between partial derivations
  - best derivation vs. best reference derivation outside beam
- Note: a reference derivation may skip a bin (multi-word phrase translation)

$\rightarrow$ only stop when no hope that reference derivation will be in a future stack

Max Violation

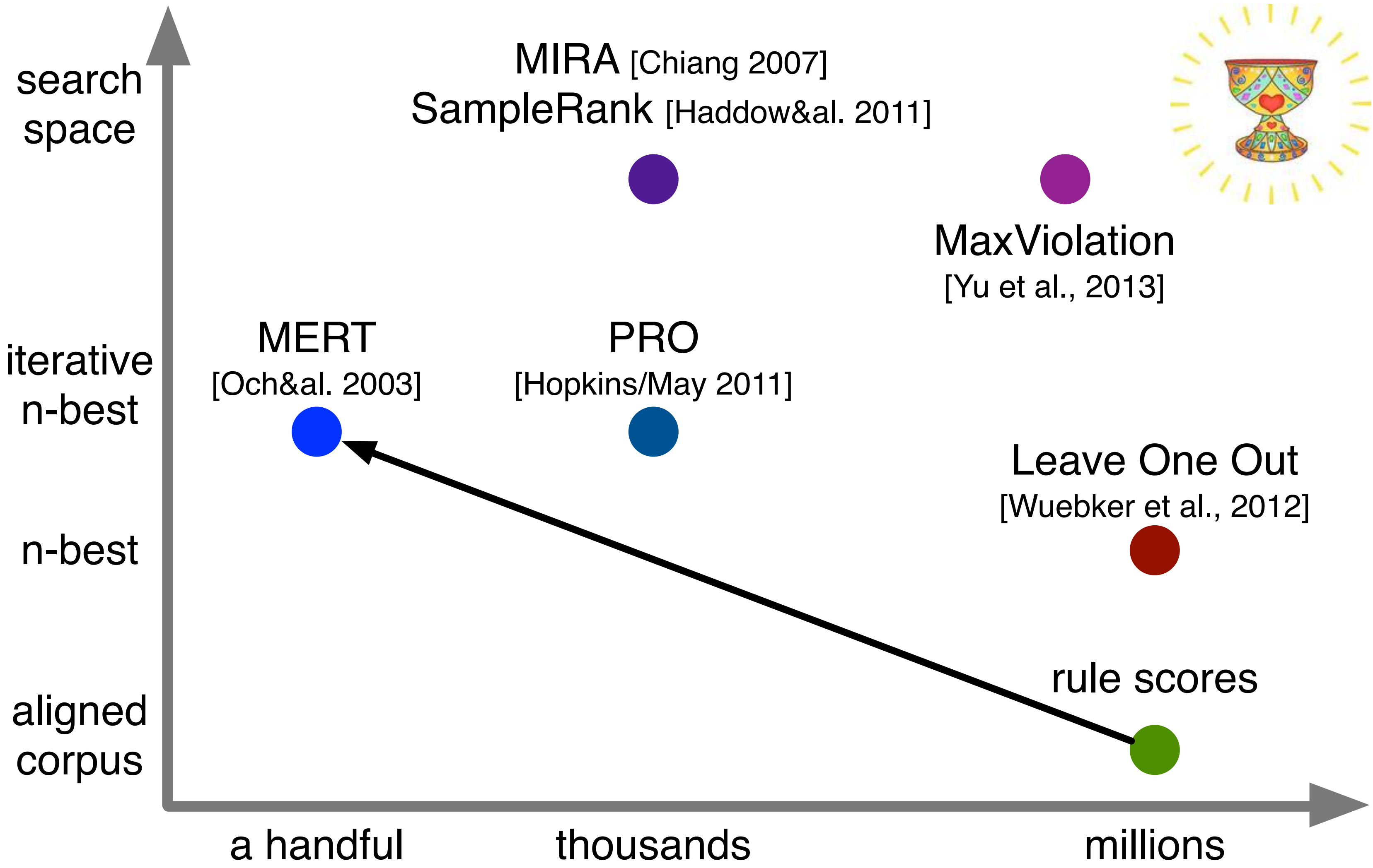


- Complete search process
- Keep best reference derivations
- Maximum violation update
  - find stack where maximal model score difference between
    - ∗ best derivation
    - ∗ best reference derivation
  - update between those two derivations

Max Violation

- Shown to be successful [Yu et al., 2013]
  - optimization over full training corpus
  - over 20 million features
  - relatively small data conditions (5-9 millions words)
  - gain: +2 BLEU points
- Features
  - rule id
  - word edge features (first and last word of phrase), defined over words, word clusters, or POS tags
  - combinations of word edge features
  - non-local features: ids of consecutive rules, rule id + last two English words
- Address overfitting: leave-one-out or singleton pruning

Summary


search space
iterative n-best
n-best
aligned corpus
a handful
thousands
millions
MIRA [Chiang 2007]
SampleRank [Haddow&al. 2011]
MaxViolation
[Yu et al., 2013]
MERT
[Och&al. 2003]
PRO
[Hopkins/May 2011]
Leave One Out
[Wuebker et al., 2012]
rule scores