The Operation Sequence Model

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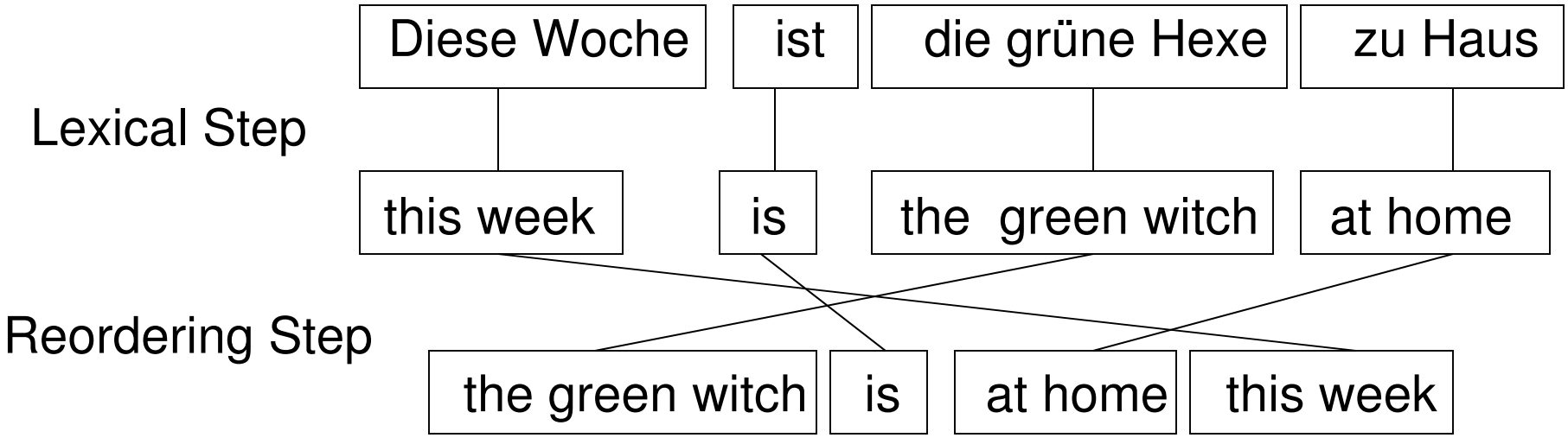
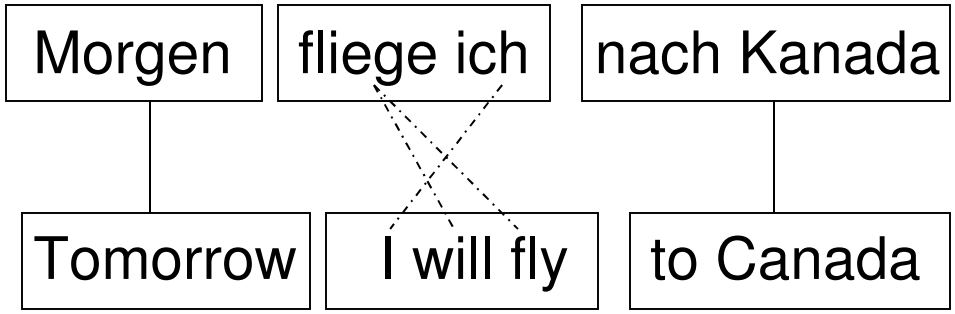
Phrase-based SMT

- State-of-the-art for many language pairs

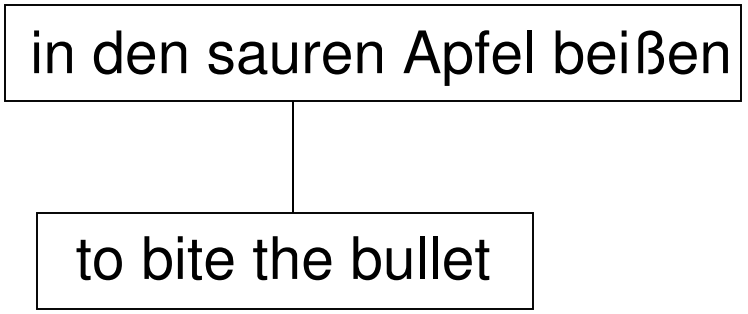


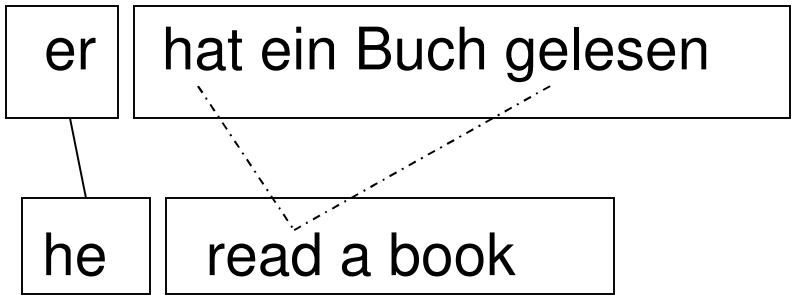
Benefits of Phrase-based SMT

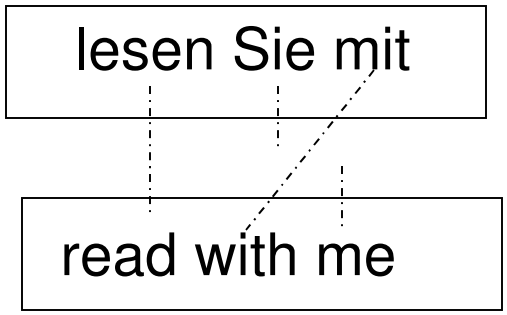
1. Local reordering



2. Idioms





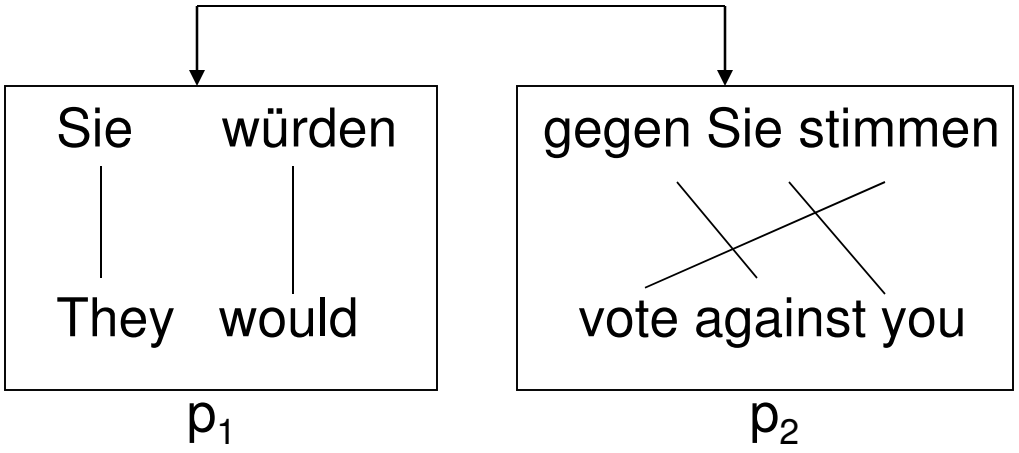


3. Discontinuities in phrases

4. Insertions and deletions

Phrase-based model: Problems

- Strong phrasal independence assumption



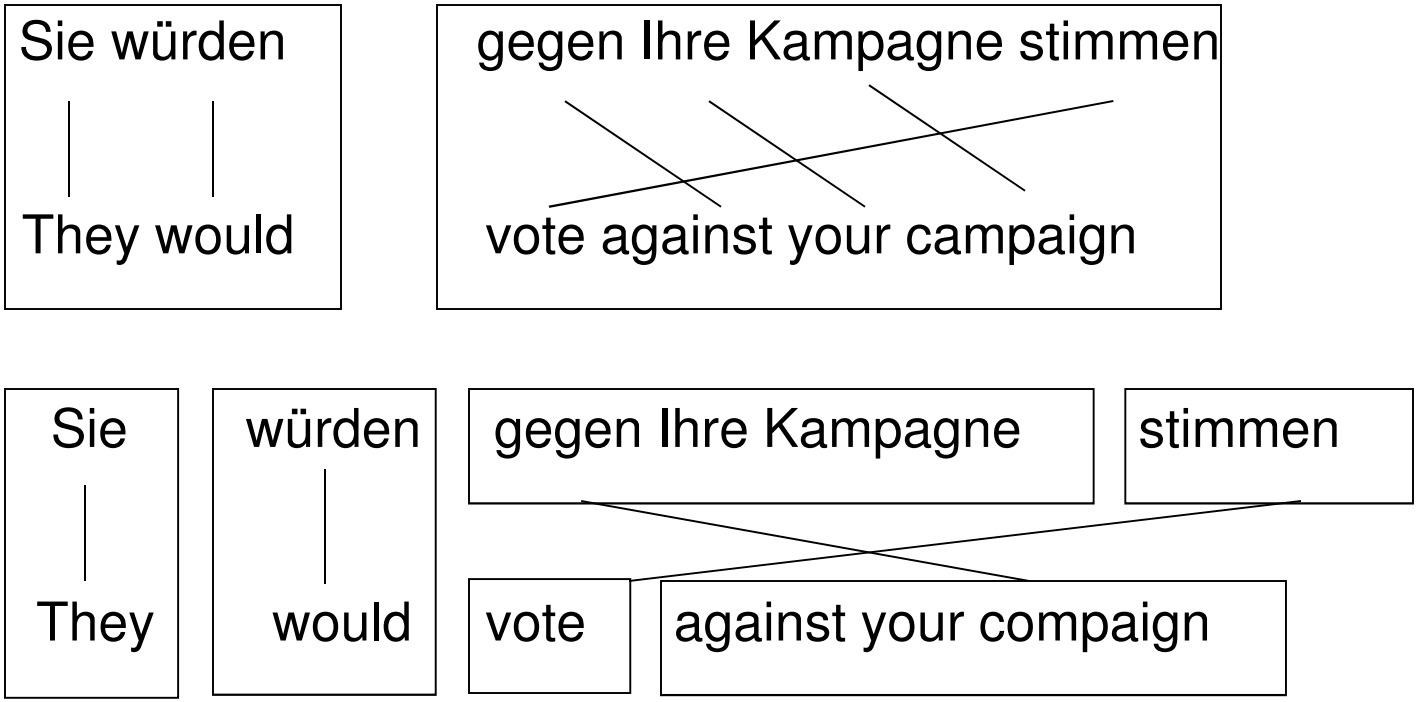
Cannot capture the dependency outside phrases

$Test_1$: Die Menschen würden gegen Sie Stimmen

$Test_2$: Die Menschen würden für die Legalisierung der Abtreibung in Kanada stimmen

Phrase-based model: Problems

- Spurious phrasal segmentation: Many possible segmentations



Phrase-based model: Problems

- Lexicalized reordering models are weak
  - Context insensitivity: Orientation only depends upon current phrase
  - Data Sparsity and Ambiguity: Short phrases have multiple orientation
    - 92.4% one word, 54% of two word Zh-EN phrases are ambiguous Li et. al (2014)
    - Most of the phrases are observed only once Cherry (2013)
  - Performs poorly with long rang reorderings
    - Heavily depends on language model
    - Most phrase-based systems use a DL=6

Motivation: Long Distance Reordering in German-to-English SMT

- Structure of main clauses in German:
  - … V2 MITTELFELD VC
- The “mittelfeld”, what’s between V2 and VC, can be arbitrarily long
- Er V2:hat ein Buch VC:gelesen → He read a book
  - hat … gelesen = read
  - Er hat gestern Nachmittag ein spannendes Buch gelesen
  - Er hat gestern Nachmittag mit seiner kleinen Tochter, die aufmerksam zugehört hat, und seinem Sohn, der lieber am Computer ein Videogame gespielt hätte, ein spannendes Buch gelesen

Motivation: Long Distance Reordering in German-to-English SMT

- Er hat ein Buch gelesen → He read a book

- Er hat gestern Nachmittag mit seiner kleinen Tochter, die aufmerksam zugehört hat, und seinem Sohn, der lieber am Computer ein Videogame gespielt haette, ein spannendes Buch gelesen

- We want a model that
  - captures ”hat … gelesen = read”
  - captures the generalization that an arbitrary amount of stuff can occur between V2:hat and VC:gelesen
  - is a simple left-to-right model

Overview

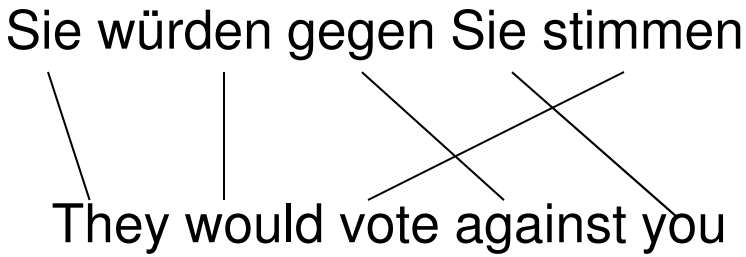
- Operation Sequence Model (OSM), a new SMT model that
  - Captures benefits of existing SMT frameworks
    - Phrase-based and N-gram-based SMT
    - Addresses their shortcomings
  - Has the ability to memorize phrase pairs
  - Robust search mechanism
  - Captures source and target information across phrasal boundaries
  - Does not have spurious phrasal segmentation ambiguity

- Unique property of OSM: Better reordering mechanism
  - Coupling of translation and reordering (like syntax-based SMT)
  - Ability to capture very long distance reordering

Introduction

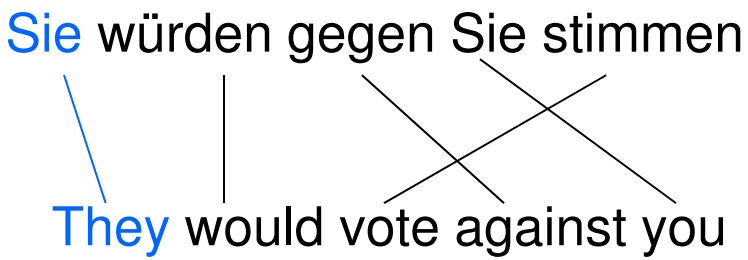
- Generation of bilingual sentence pair through a sequence of operations
- Operation: Translate or Reorder
- P(E, F, A) = Probability of the operation sequence required to generate the bilingual sentence pair

Example



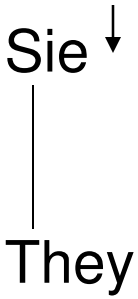
- Rules:
  - Simultaneous generate of source and target sentences
  - Generation is done in order of the target sentence
  - Reorder when source and target are in the same order

Example

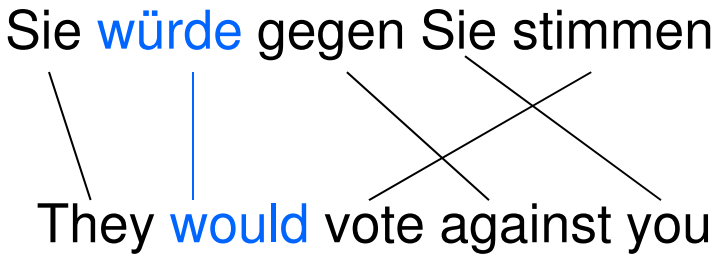


Operations

o_1: Generate (Sie – They)



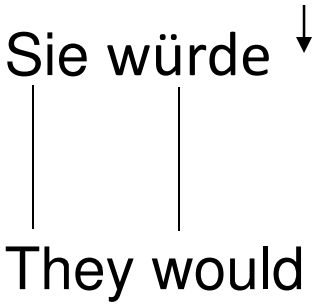
Example



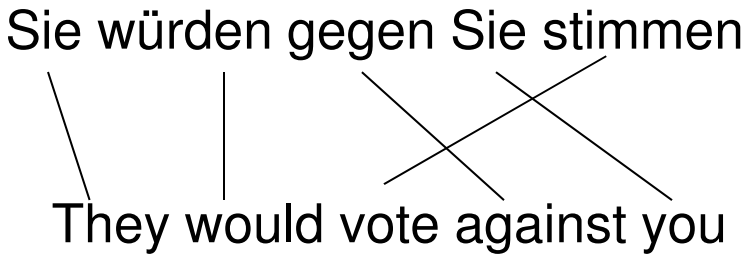
Operations

o_1 Generate (Sie, They)

o_2 Generate (würde, would)

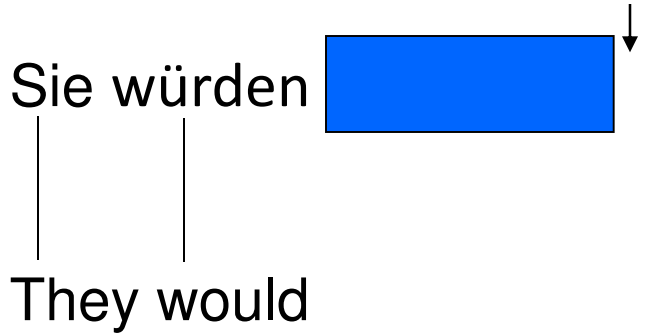


Example

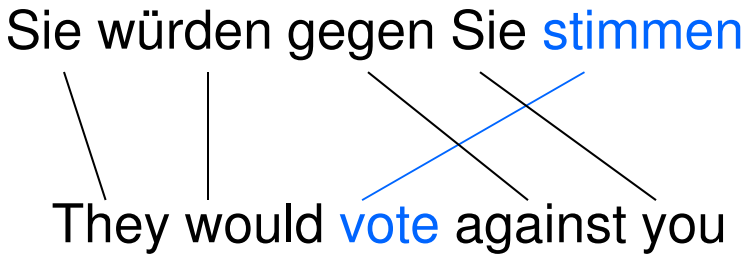


Operations

- o_1 Generate (Sie, They)
- o_2 Generate (würden, would)
- o_3 Insert Gap

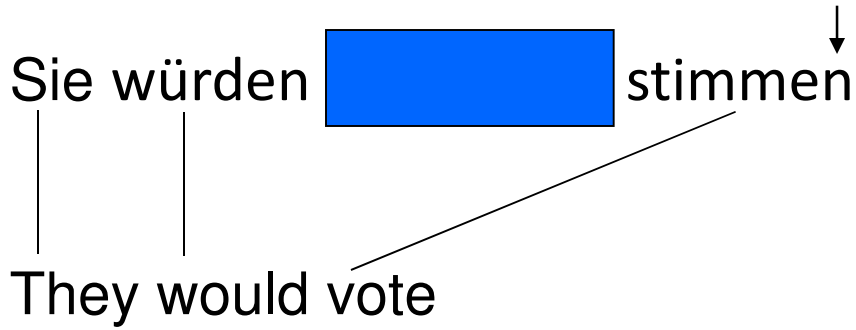


Example

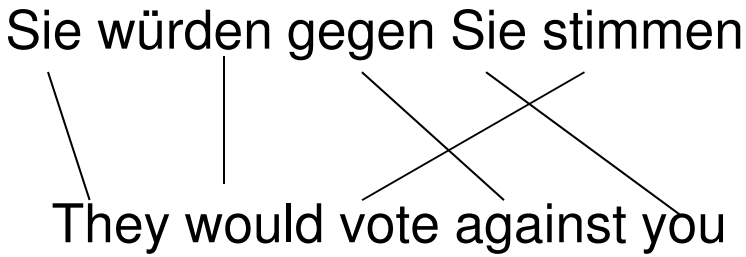


Operations

- o_1 Generate (Sie, They)
- o_2 Generate (würden, would)
- o_3 Insert Gap
- o_4 Generate (stimmen, vote)

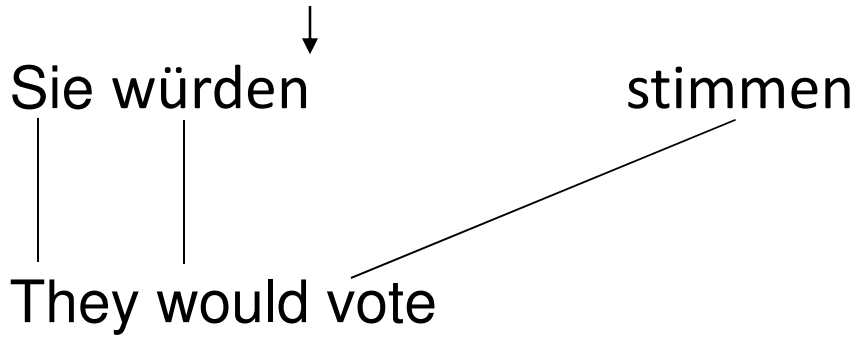


Example

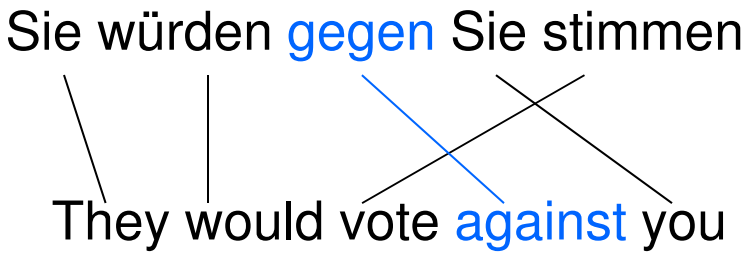


Operations

- o_1 Generate (Sie, They)
- o_2 Generate (würden, would)
- o_3 Insert Gap
- o_4 Generate (stimmen, vote)
- o_5 Jump Back (1)

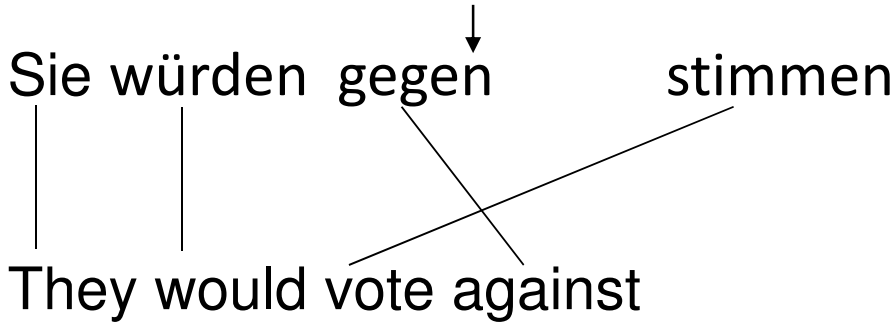


Example

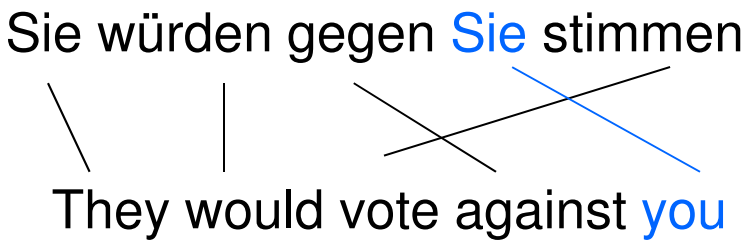


Operations

- o_1 Generate (Sie, They)
- o_2 Generate (würden, would)
- o_3 Insert Gap
- o_4 Generate (stimmen, vote)
- o_5 Jump Back (1)
- o_6 Generate (gegen, against)

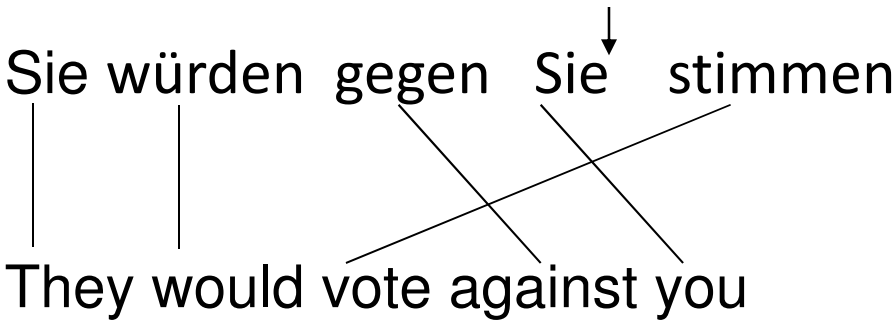


Example



Operations

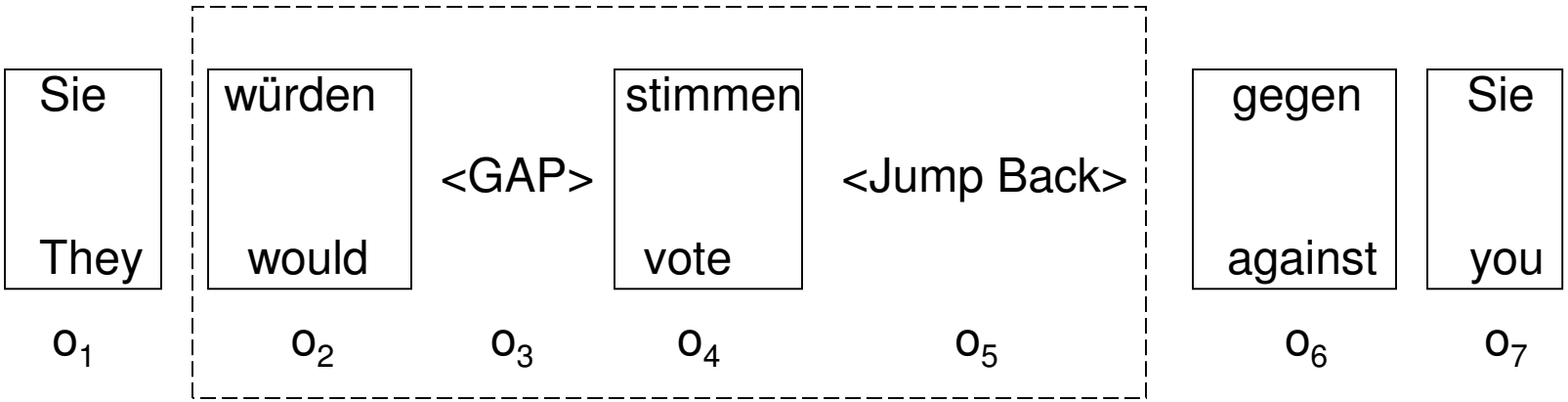
- o_1 Generate (Sie, He)
- o_2 Generate (würde, would)
- o_3 Insert Gap
- o_4 Generate (stimmen, vote)
- o_5 Jump Back (1)
- o_6 Generate (gegen, against)
- o_7 Generate (Sie, you)



Model

- Joint probability model over operation sequences

$$p_{osm}(F, E, A) = p(o_1^J) = \prod_{j=1}^{J} p(o_j | o_{j-n+1}, \ldots, o_{j-1})$$



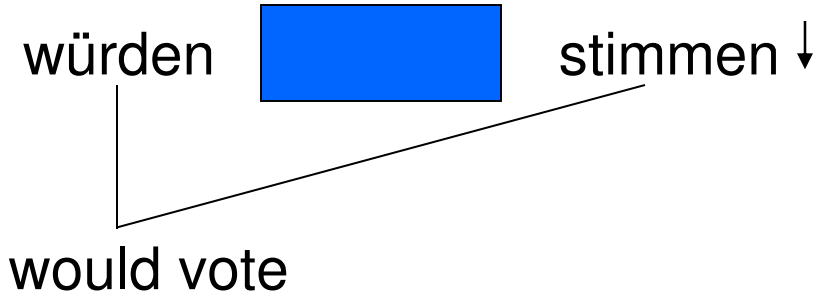
Context window: 5-gram model

Useful properties of OSM

- Capture source and target context across phrasal boundaries
  - Simultaneously generate source and target units
- Model does not have spurious ambiguity
  - Model is based on minimal translation units (MTUs)
- Better reordering mechanism
  - Uniformly handles local and non-local reorderings
  - Strong coupling of lexical generation and reordering

Example of a learned pattern

- Operations
  - Generate (würden, would)
  - Insert Gap
  - Generate (stimmen, vote)

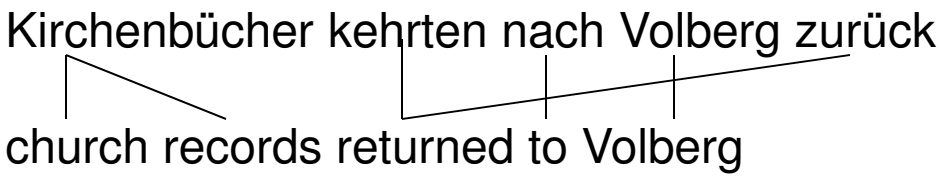


- Can generalize to
  - Die Menschen würden dafür stimmen
  - Die Menschen würden gegen meine Außenpolitik stimmen
  - Die Menschen würden für die Legalisierung der Abtreibung in Kanada stimmen

- Equivalent to hierarchical phrase “würden X stimmen – would vote X”

- Gaps can be created recursively
  - Multiple gaps can occur simultaneously

Useful properties of OSM



- Handling Discontinuities
  - kehrten [redacted] zurück – return
  - Generate (kehrten…[zurück], returned) – Insert Gap – Continue Cept
  - letzte Woche kehrten die Kinder zu ihren biologischen Eltern zurück

- Insert and Deletion Models (learning with context)
  - Source word deletion
  - Target word insertion
  - Lesen Sie mit – read with me
  - Generate (Lesen, read) → Generate Source Only (Sie) → Generate (mit, with) → Generate Target Only (me)

List of Operations

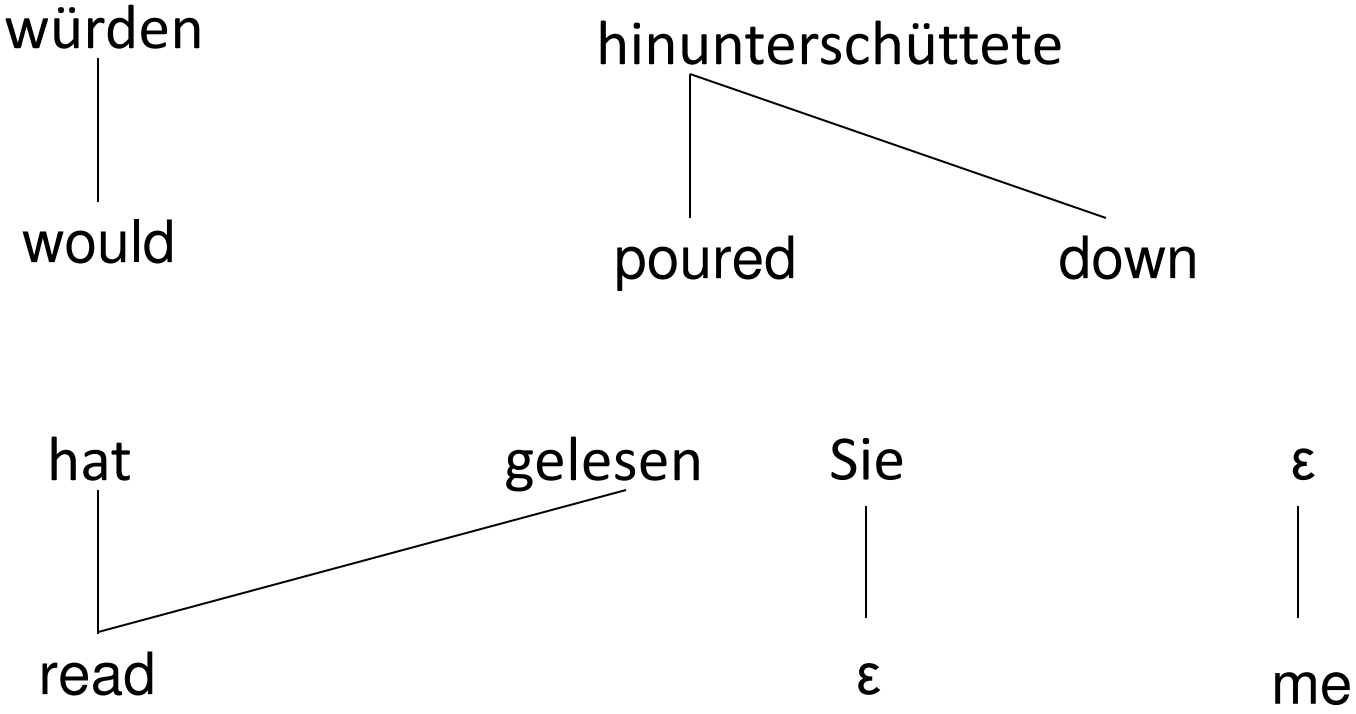
- 5 Translation Operations
  - Generate (X,Y)
  - Continue Source Cept
  - Generate Identical
  - Generate Source Only (X)
  - Generate Target Only (Y)
- 3 Reordering Operations
  - Insert Gap
  - Jump Back (N)
  - Jump Forward
- Corpus Conversion Algorithm

Operation Sequence Model (OSM) in a nutshell

- Aspects that are similar to N-gram-based SMT
  - Translation as sequential generation of a sentence pair
  - Generation is in target order
  - Sequential Markov model
  - MTU-based: Lexical operations generate MTUs
- What's new
  - Sequence of operations (as opposed to sequence of MTUs)
  - Two types of operations
    - Lexical operations
    - Reordering operations
  - Model based on minimal units, decoder based on phrases

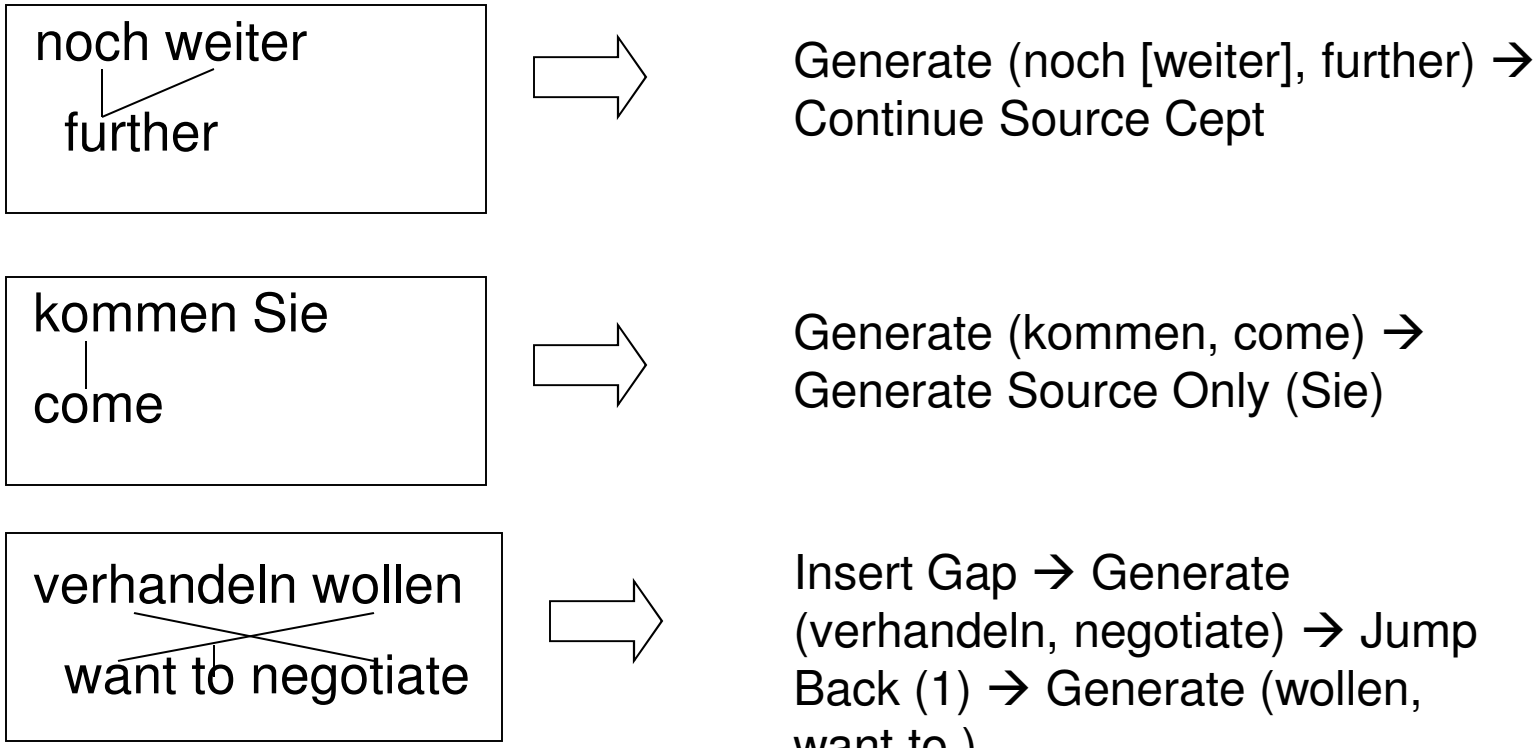
MTU = Minimal Translation Unit

- Model is based on MTUs
- Definition: MTU = connected component of the alignment bigraph



OSM learns phrases as operation sequences

- Although model is based on MTUs, we can memorize phrases



Decoders

- Cept-based decoder (or MTU-based decoding)
- Phrase-based decoder
- Moses

Decoding

- MTU-based decoding
  - extends current hypothesis by one MTU
- Phrase-based decoding
  - extends current hypothesis by one phrase
- Phrase-based decoding works better than MTU-based decoding
  - Example: Wie heißen Sie – What is your name
  - MTUs: Wie/What-is, heißen/name, Sie/your
  - Wie/What-is is very unlikely, so it will get pruned (or you need a large stack size)
  - The phrase pair: “Wie heißen Sie – What is your name” is likely
    - Makes search easier

Advantages of phrase-based decoding versus MTU-based decoding

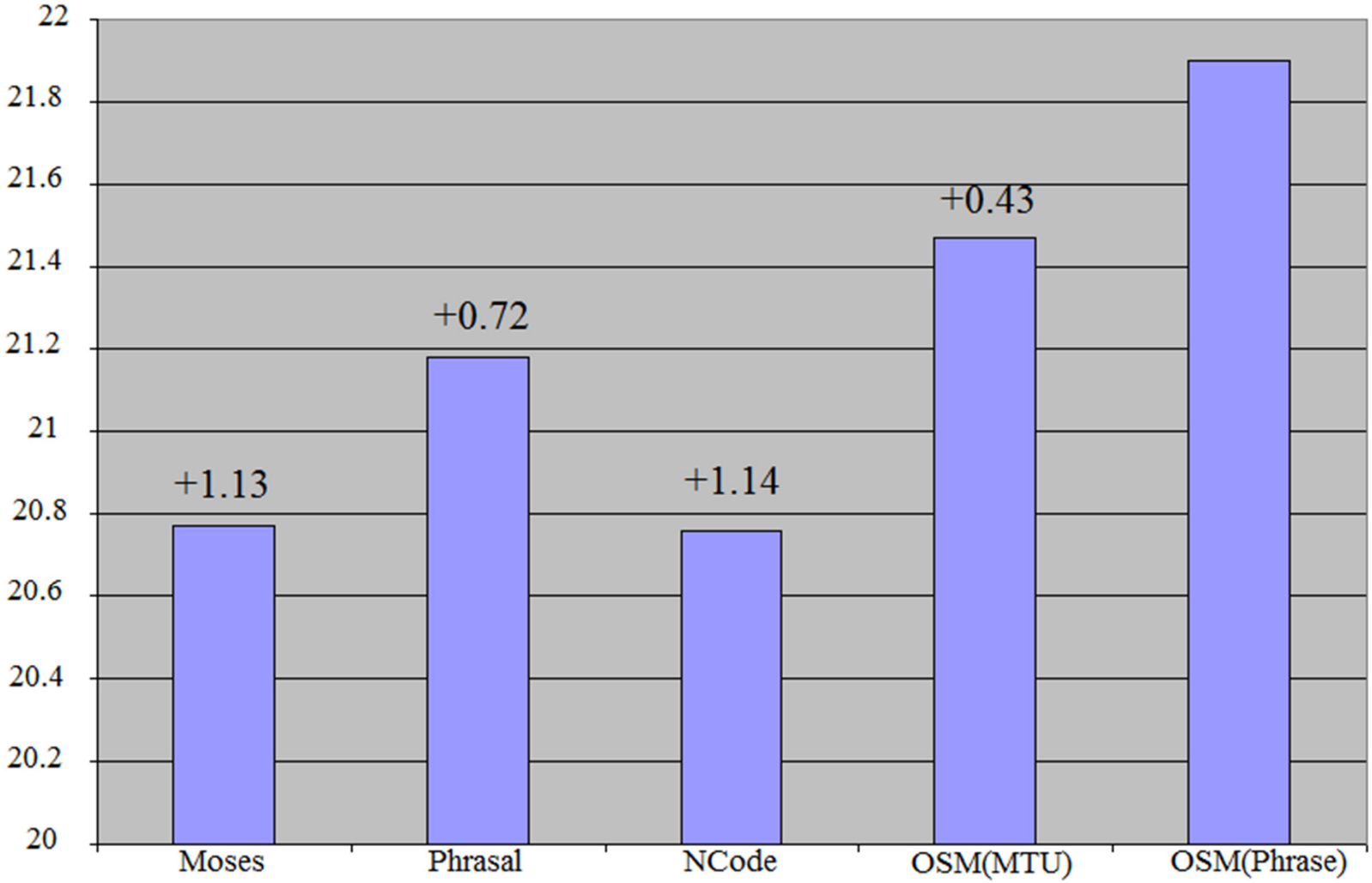
- Better future cost estimation
- Better translation coverage
- Lower beam size
- Unaligned target words
- Discontinuous target words

Baseline systems

- Moses
  - with lexicalized reordering (Koehn et. al 2005)
- Phrasal
  - with hierarchical lexicalized reordering (Galley and Manning 2008)
  - discontinuous phrases (Galley and Manning 2010)
- NCode
  - with lexicalized reordering (Crego and Yvon 2010)

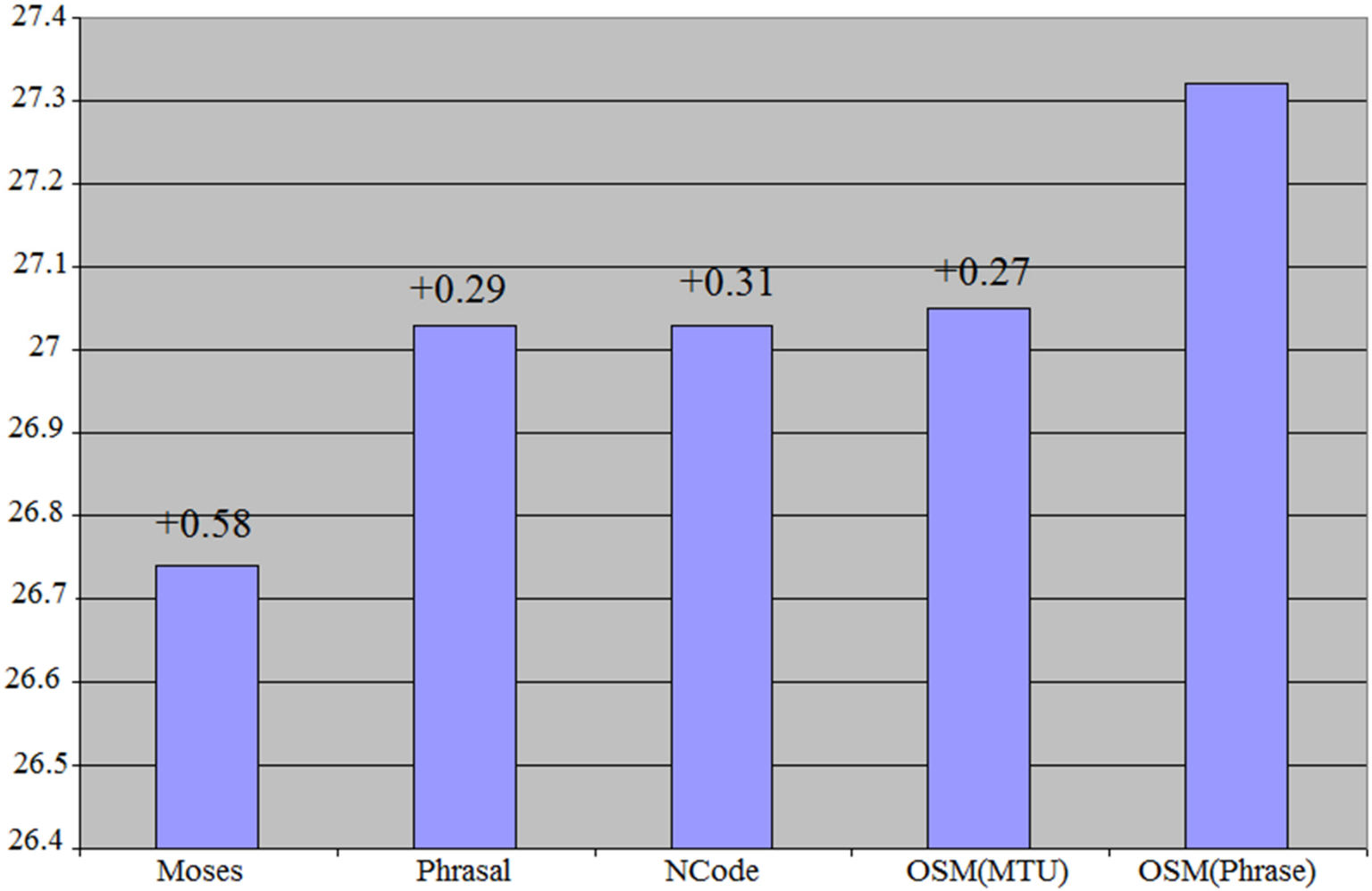
German-to-English

- Significant improvements over all baselines



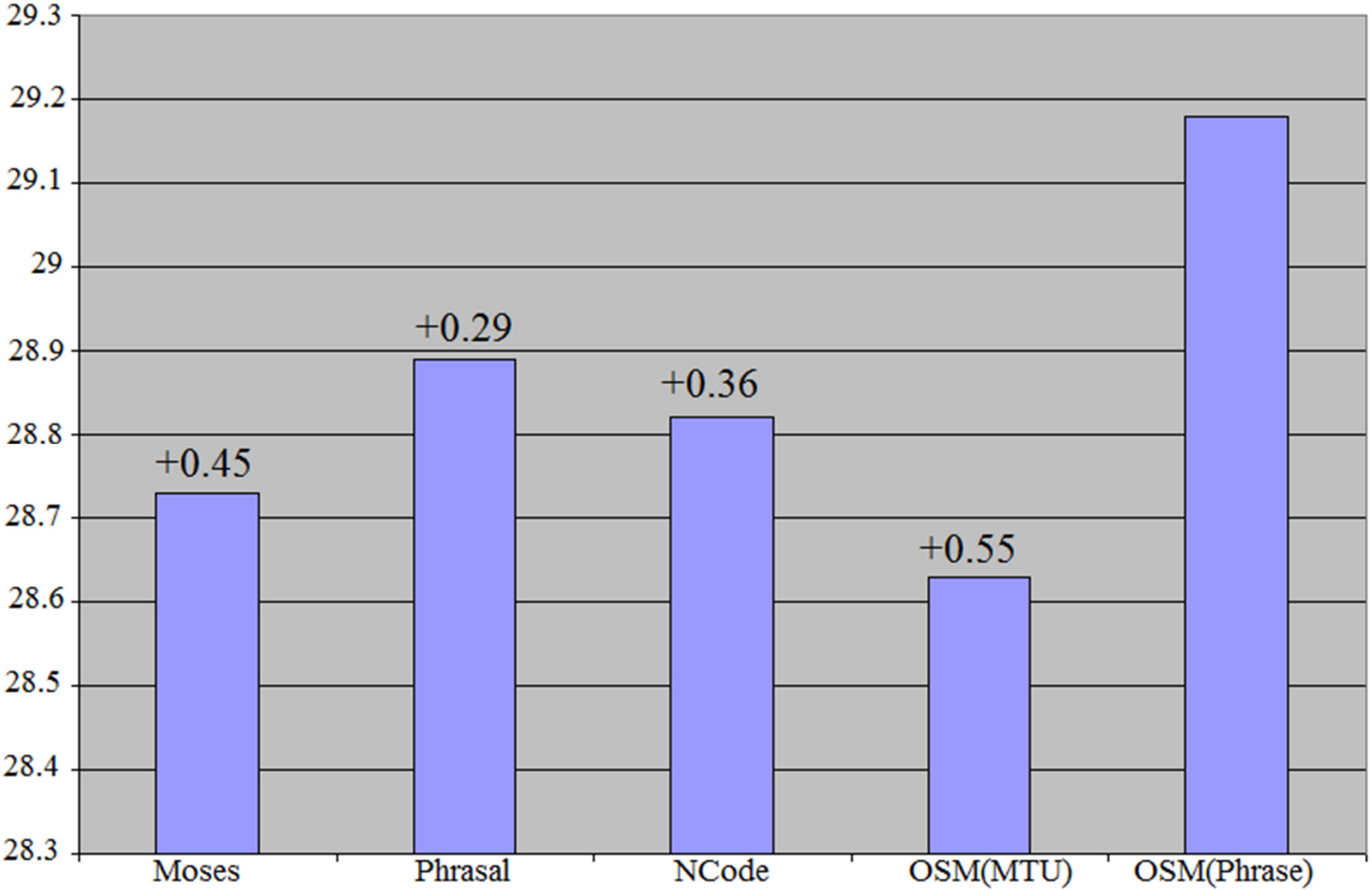
French-to-English

- Significant improvement in 11/16 cases



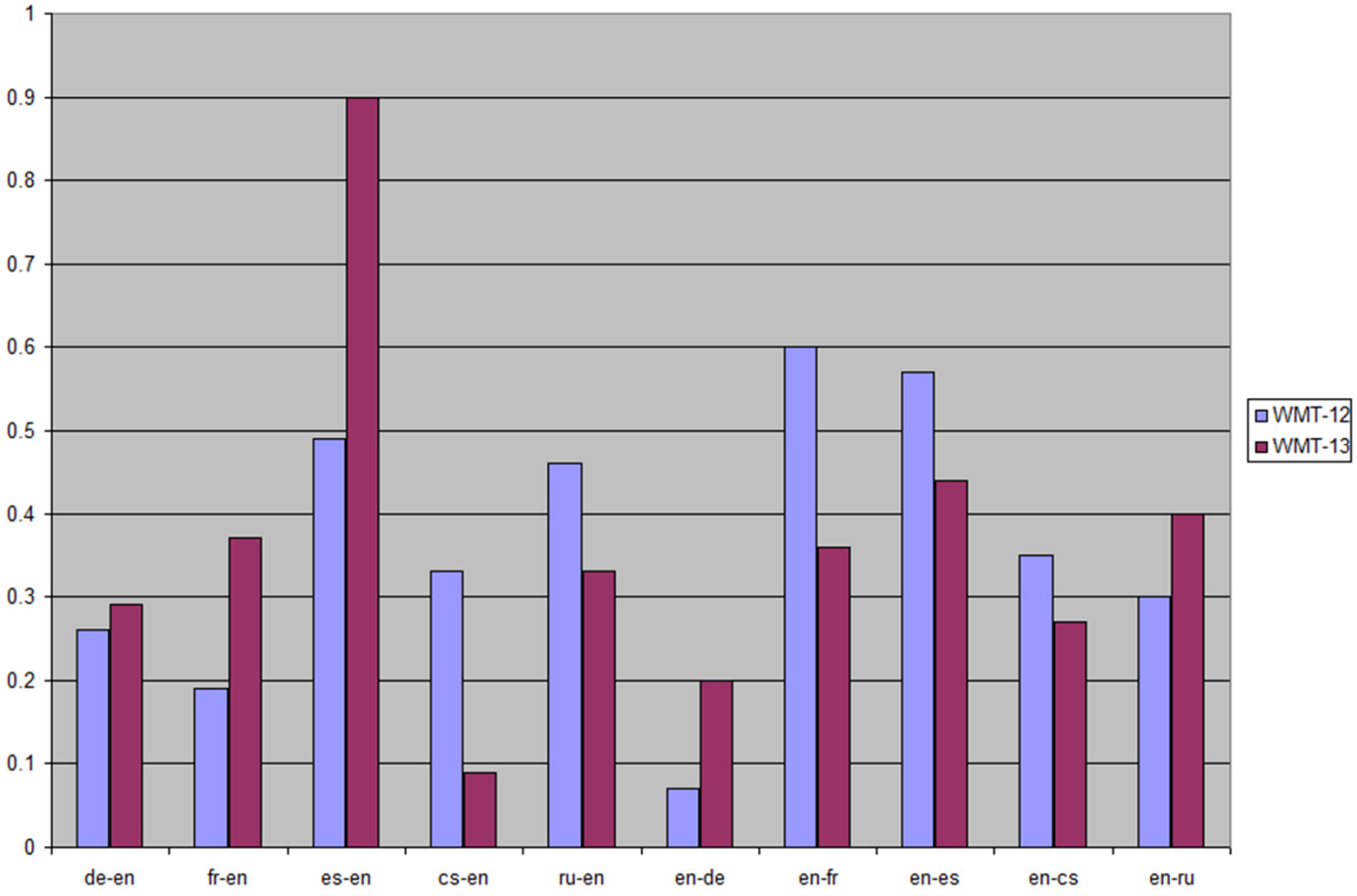
Spanish-to-English

- Significant improvement in 12/16 cases



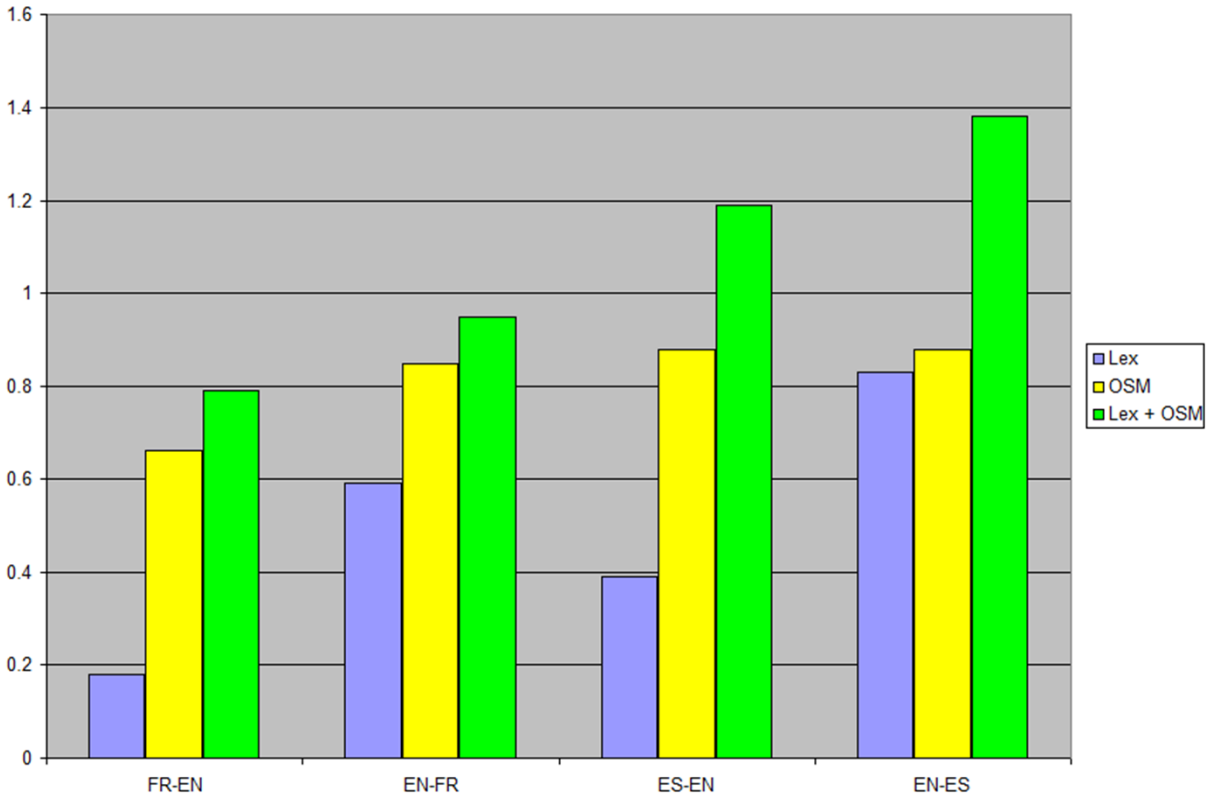
Integration into Moses (Durrani et al., ACL2013)

- Large scale evaluation (WMT-12/13)
- Average gain of +0.40 over submission quality baseline system over 10 language pairs – Significant gains in most cases



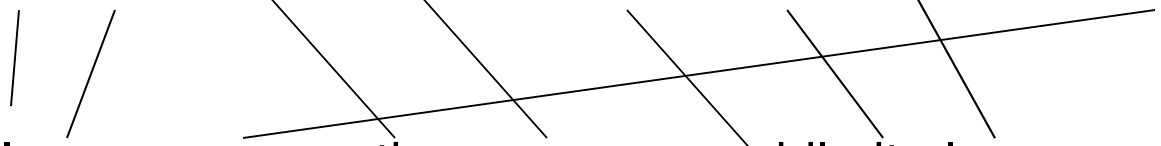
Comparison with lexicalized reordering model

- Baseline = Distortion based reordering model
  - OSM outperforms lexical reordering modeling in all four language pairs (yellow vs. purple)
  - Gains are additive (Green)



Generalized OSM Models

Ich kann die Sequenz während sie abläuft umstellen



I can rearrange the sequences while it plays

Wir können die Bücher umstellen, während er liest

We can rearrage the books while he reads

Ich kann  umstellen

PPER VMFIN  VVINF

I can rearrange

PP MD VB

Generalized OSM Models

- POS tags, Morphological Tags, Automatic Word Clusters (mkcls)

- IWSLT 2013
  - Morphological tags +1.06 for EN-DE, +0.63 for DE-EN
  - Word clusters
    - Experiments over 8 language pairs
    - Gains up to +2.02 BLEU points
  - Average OSM look-up improved from bigram to 5-gram model when using POS and automatic clusters

Summary: The OSM model …

- Integrates translation and reordering in a single generative story
- Uses bilingual context (like N-gram based SMT)
- Has an improved reordering mechanism
  - Models local and non-local dependencies uniformly
  - Takes previous translation decisions into account (like N-gram SMT)
  - Takes previous reordering decisions into account (unlike N-gram SMT)
  - Has ability to memorize lexical triggers (like phrase-based SMT)
  - Considers all possible reorderings during search

Summary: The OSM model …

- Does not have spurious phrasal segmentation (like N-gram SMT)
- Does not need ad-hoc limits during search (unlike N-gram and phrase-based)
- Supports discontinuous translation units
- Handles unaligned translation units through built-in insertion and deletion models

Conclusion

- OSM = union of N-gram-based SMT and phrase-based SMT
- Phrase-based decoding+OSM is an effective combination of an MTU-based model and phrase-based-search
- Can be used as a feature in any left-to-right decoding mechanism
- Statistically significant improvements over baseline systems

Conclusion

- Model has been extended to use in tandem with factored-based models
  - Wider context
  - Better generalization
  - Improved translation and reordering decisions
- Operation sequence model is available in the latest version of Moses

References

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