An Unsupervised Method for Uncovering Morphological Chains

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Morphological Chains

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Chains to model the formation of words.

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paint → painting → paintings

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Paradigms

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Core Idea: Unsupervised discriminative model over pairs of words in the chain.

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- **Semantic features**
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- Handle **transformations.** (plan → planning)

Textual Cues

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paint	pain
paints	pains
painted	pained

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Meaning embedded as vectors.

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Task Setup

Training

Unannotated word list with frequencies

a	395134
ability	17793
able	56802
about	524355

Word Vector Learning

Large text corpus

Wikipedia

Multiple chains possible for a word.

nation → national → international → internationally

nation → national → nationally → internationally

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Different chains can share word pairs.

nation → national → international → internationally

nation → national → nationalize

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national

Word (**w**)

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Treat word-parent pairs separately

national → nation | Suffix

Word (**w**) | Parent (**p**) | Type (**t**)

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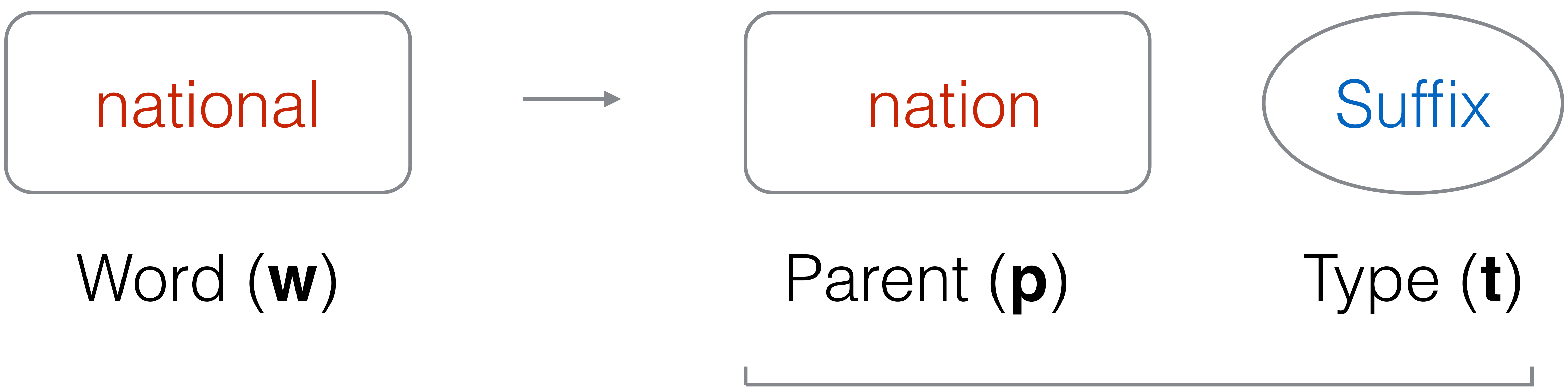

Independence Assumption

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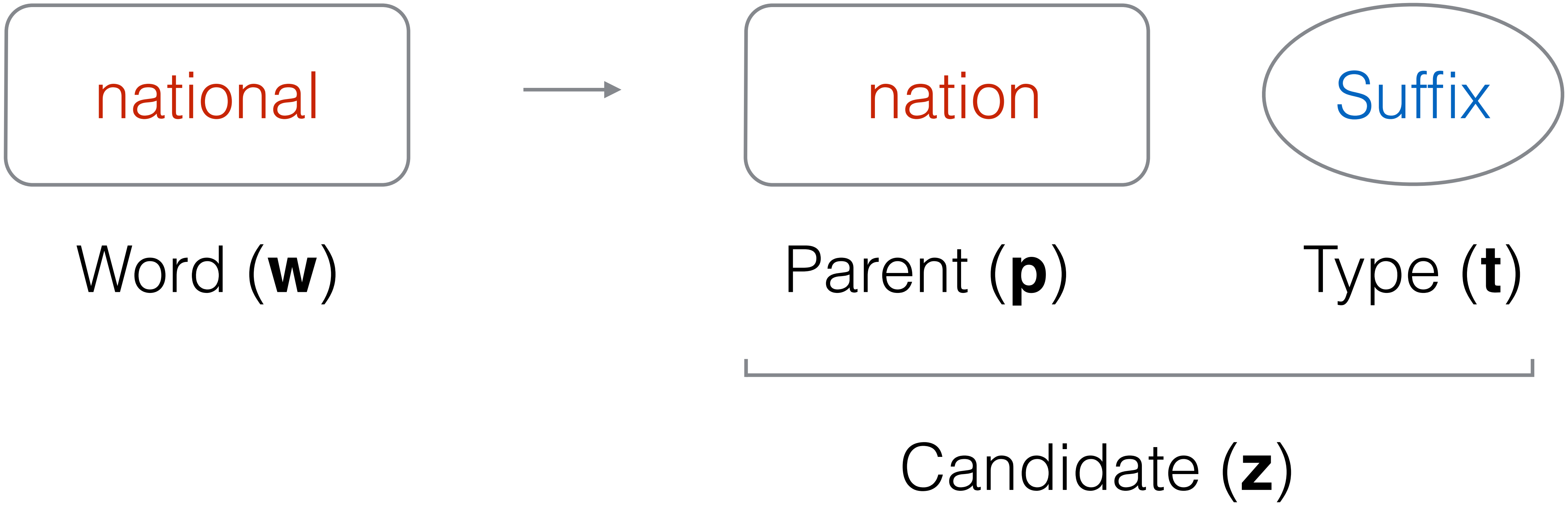
national → nation Suffix

Word (**w**) Parent (**p**) Type (**t**)

Candidate (**z**)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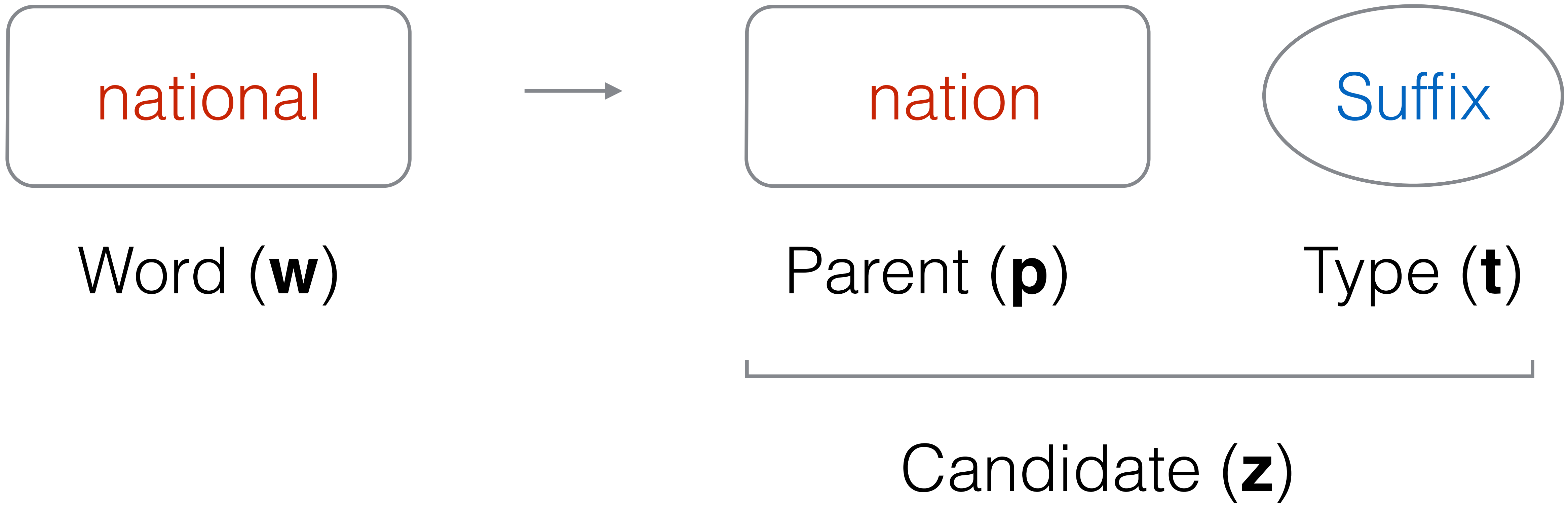

$$P(w, z) \propto e^{\theta \cdot \phi(w, z)}$$

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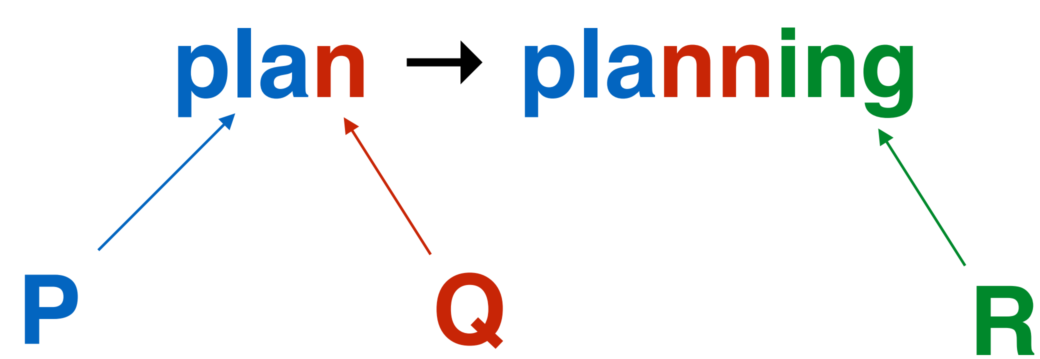
Types - **Prefix, Suffix, Transformations, Stop.**

Transformations

- Templates for handling changes in stem during addition of affixes.

  - Repetition template: **PQ → PQQR** (for each Q in alphabet). Ex.



  - Feature template for each transformation.

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- These three do well for a range of languages and are computationally tractable: max $O(|\Sigma|^2)$ for alphabet Σ

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Segment	Cosine Similarity
p	0.095
pl	-0.037
pla	-0.041
play	**0.580**
playe	0.000
player	1.000

Cosine similarity with *player*

Learning

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$$\prod_w P(w) = \prod_w \sum_z P(w, z) = \prod_w \sum_z \frac{e^{\theta \cdot \phi(w,z)}}{\sum_{w' \in \Sigma^*, z'} e^{\theta \cdot \phi(w', z')}}$$

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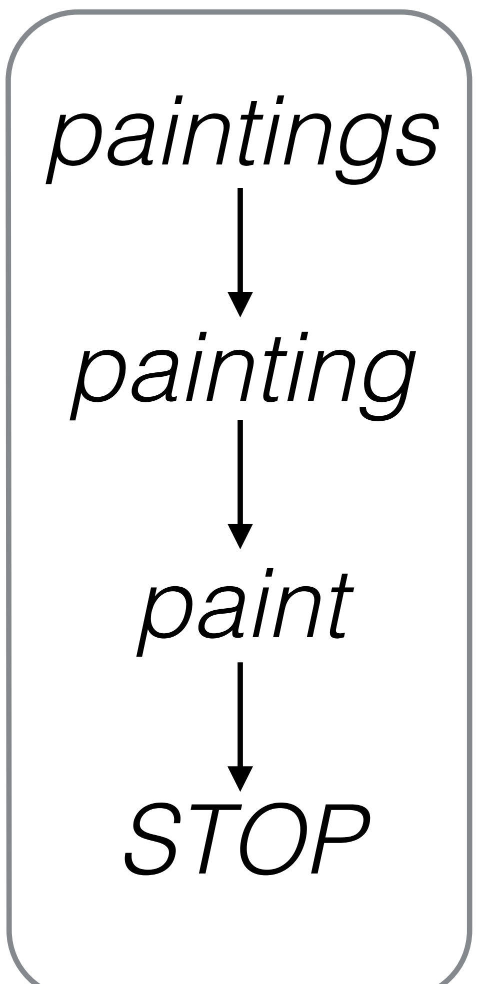
$$P(w, z) = \frac{e^{\theta \cdot \phi(w,z)}}{\sum_{w' \in N(w), z'} e^{\theta \cdot \phi(w', z')}}$$

Prediction

- Predict chain in recursive fashion (argmax parent candidate each time) till stop.



Algorithm 2 Procedure to predict a morphological chain

procedure GETCHAIN(word)
    $candidate \leftarrow \text{PREDICT}(word)$
    $parent, type \leftarrow candidate$
    if $type = STOP$ **then return** $[(word, STOP)]$
    return GETCHAIN(parent)+$[(parent, type)]$

Segmentation Experiments

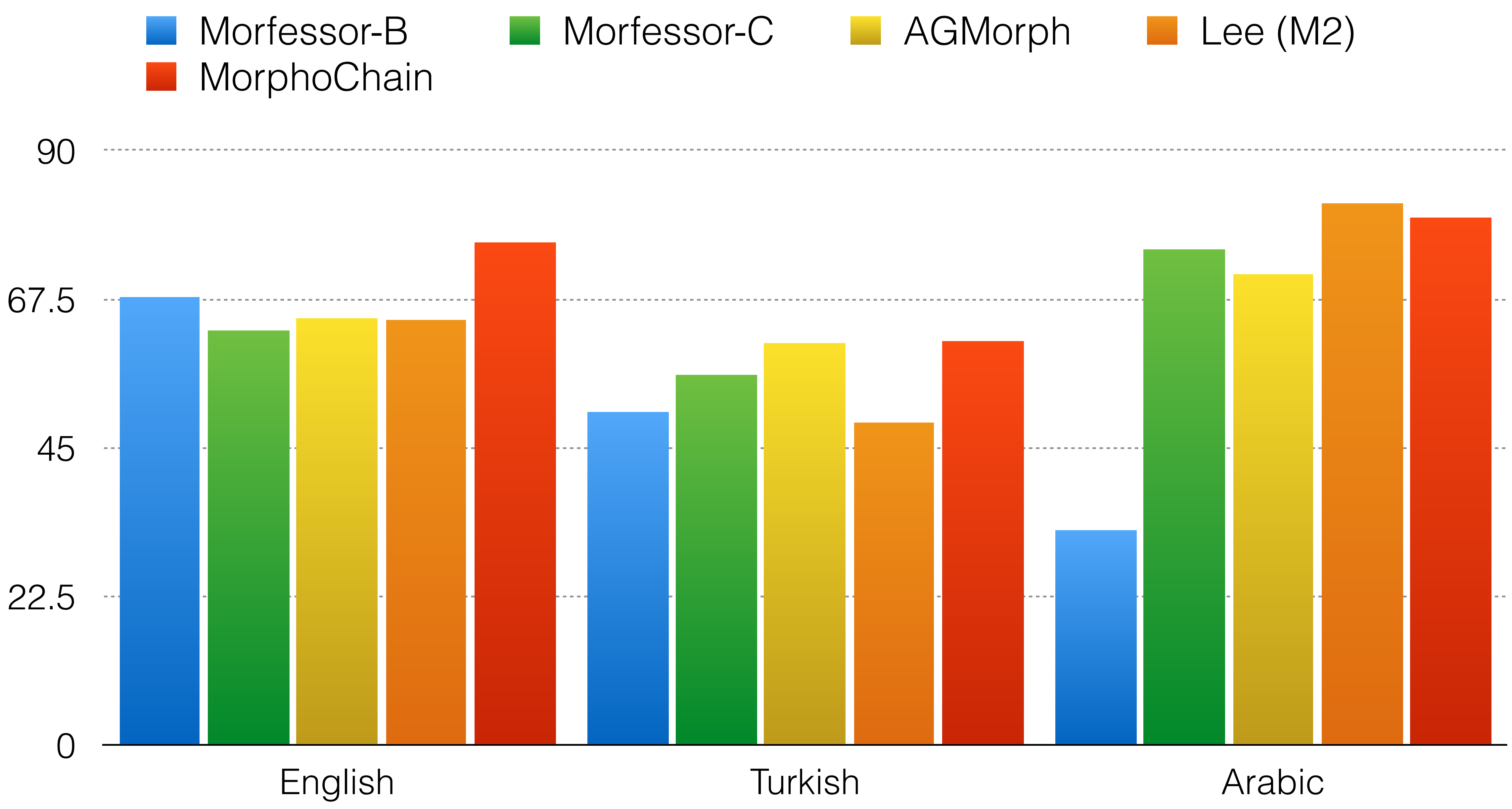
- Three languages - English, Arabic, Turkish

Lang	Train (# words)	Test (# words)	WordVec (# words)
English	MC-10 (878K)	MC-05:10 (2218)	Wikipedia (129M)
Turkish	MC-10 (617K)	MC-05:10 (2534)	BOUN (361M)
Arabic	Gigaword (3.83M)	ATB (119K)	Gigaword (1.22G)

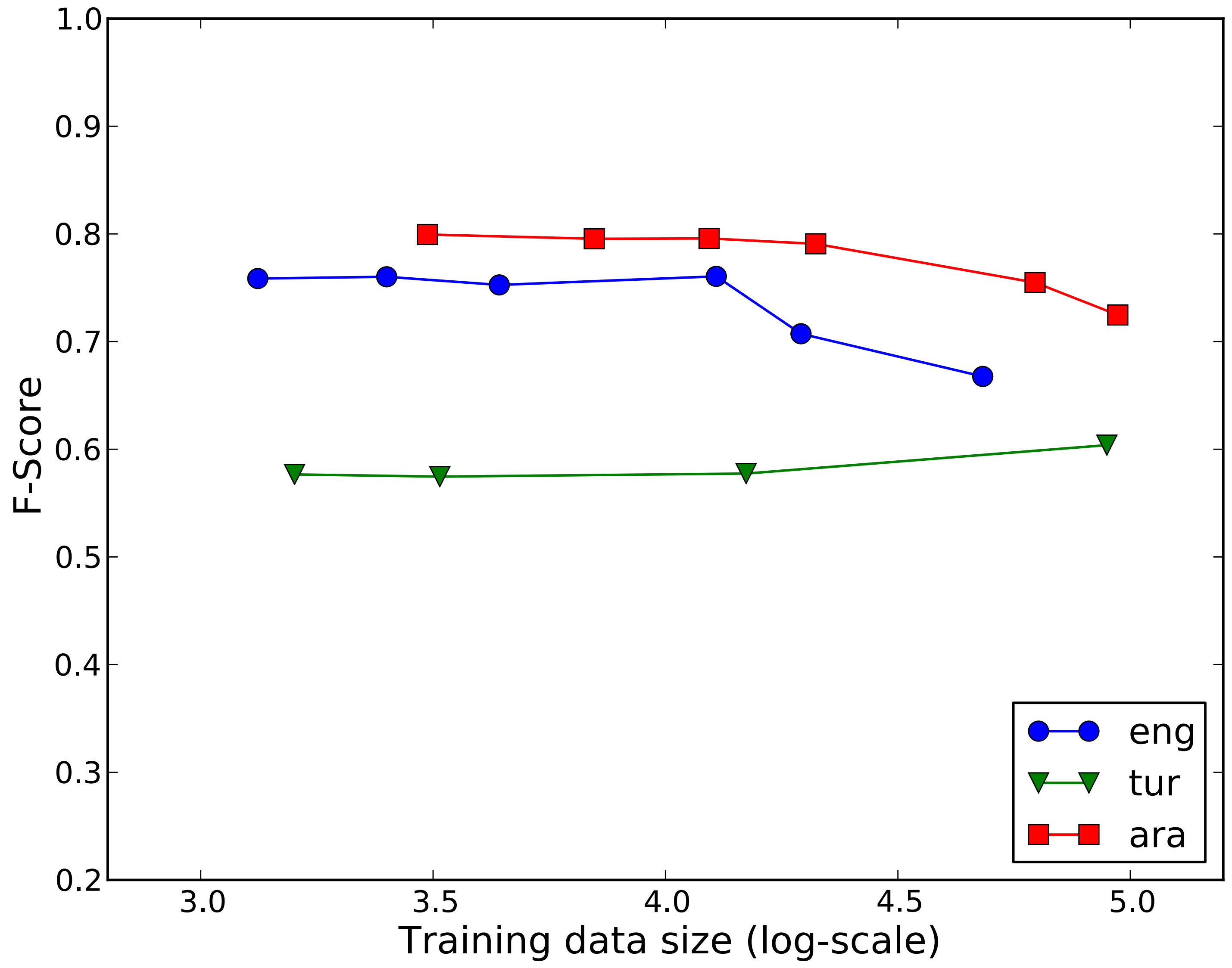
- **Evaluation:** Morphological segmentation - *Precision, Recall, F1* over individual segmentation points

- **Baselines:** Morfessor-Baseline, Morfessor CatMAP, AGMorph (Sirts and Goldwater, 2013) and Lee et al. (2011)

F1 scores on MorphoChallenge



Effect of data size



Affix Analysis

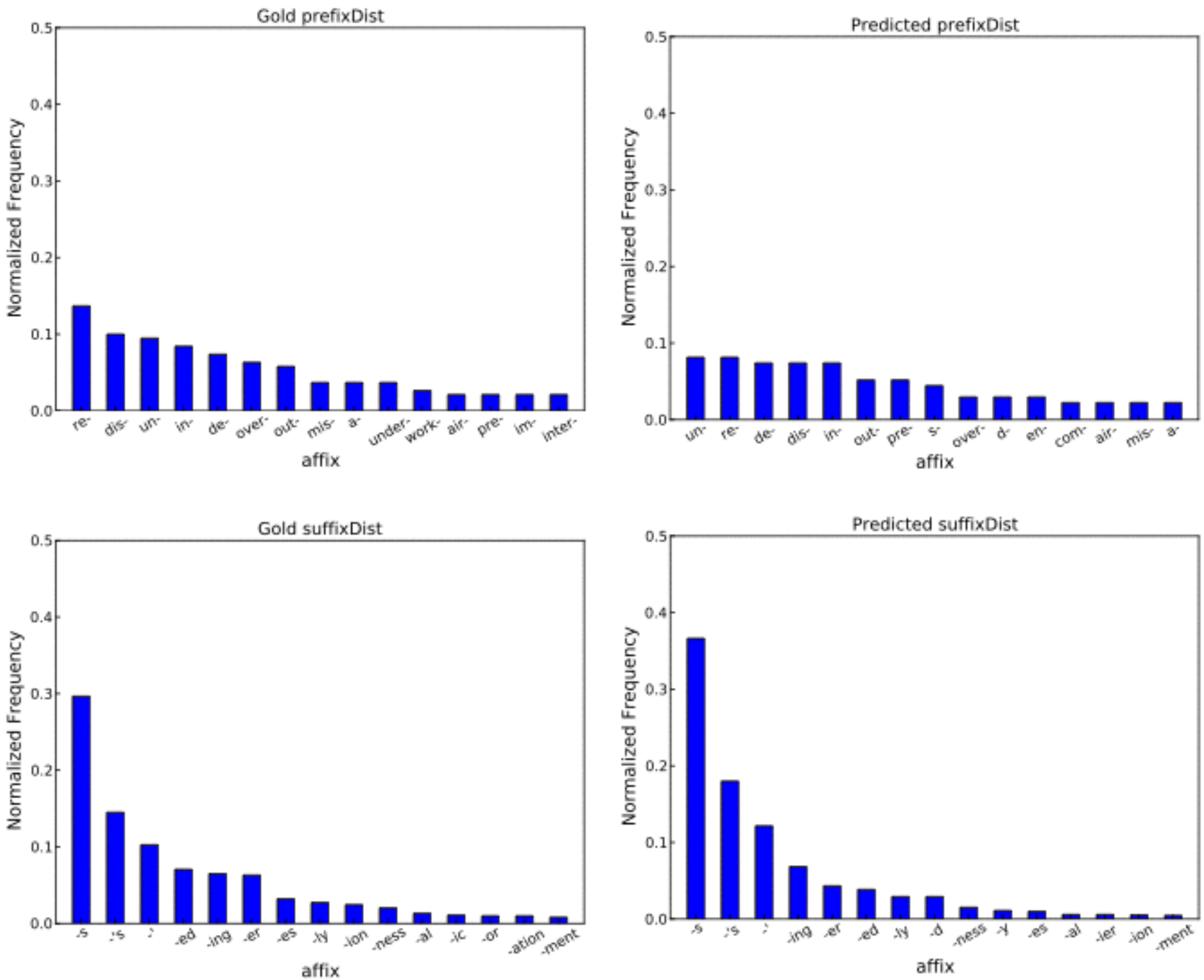


Figure 2: Comparison of gold and predicted frequency distributions of the top 15 affixes for English

Error analysis

- Errors (on a random subset of 50 words per language):

Language	**Over-segment**	**Under-segment**
English	10%	86%
Turkish	12%	78%
Arabic	60%	40%

- Most errors (58%) in Turkish due to parent words not present or having low count.
- Root template morphology of Arabic causes 14% of errors.

Sample segmentations

Correct Segmentations	
Word	**Segmentation**
salvoes	salvo-es
negotiations	negotiat-ion-s
telephotograph	tele-photo-graph
unequivocally	un-equivocal-ly
carsickness's	car-sick-ness-'s

Incorrect Segmentations		
Word	**Predicted**	**Correct**
legacies	legac-ies	lega-ci-es
sterilizing	steriliz-ing	steril-iz-ing
desolating	desolating	desolat-ing
storerooms	storeroom-s	store-room-s
tattlers	tattler-s	tattl-er-s

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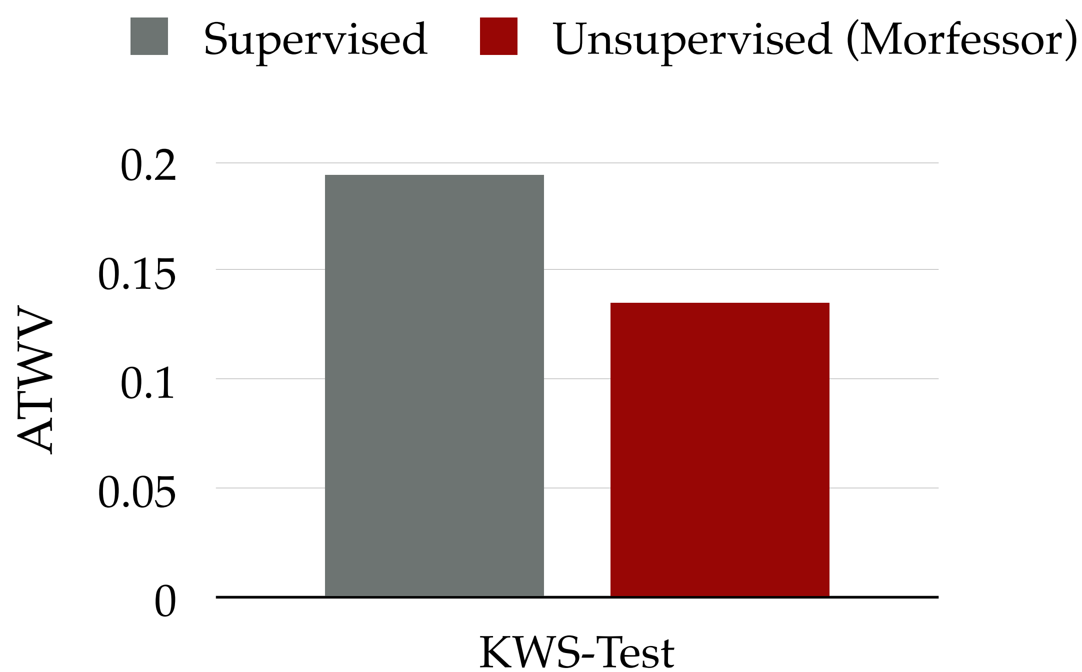

KWS Results on OOV keywords in Turkish LLP (Narasimhan et al., 2014)

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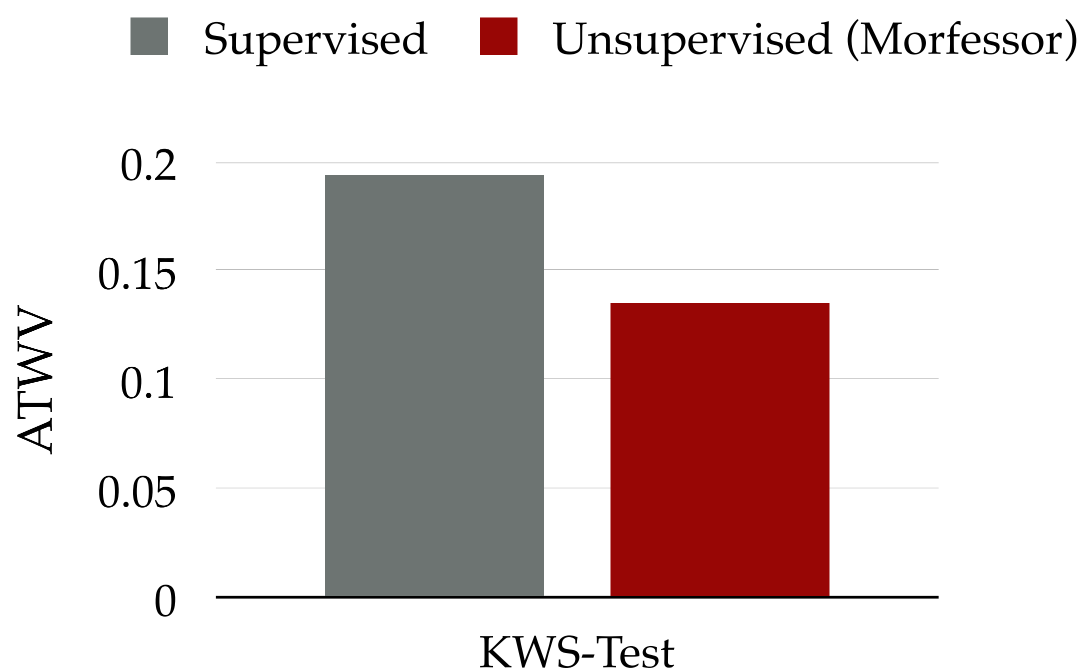
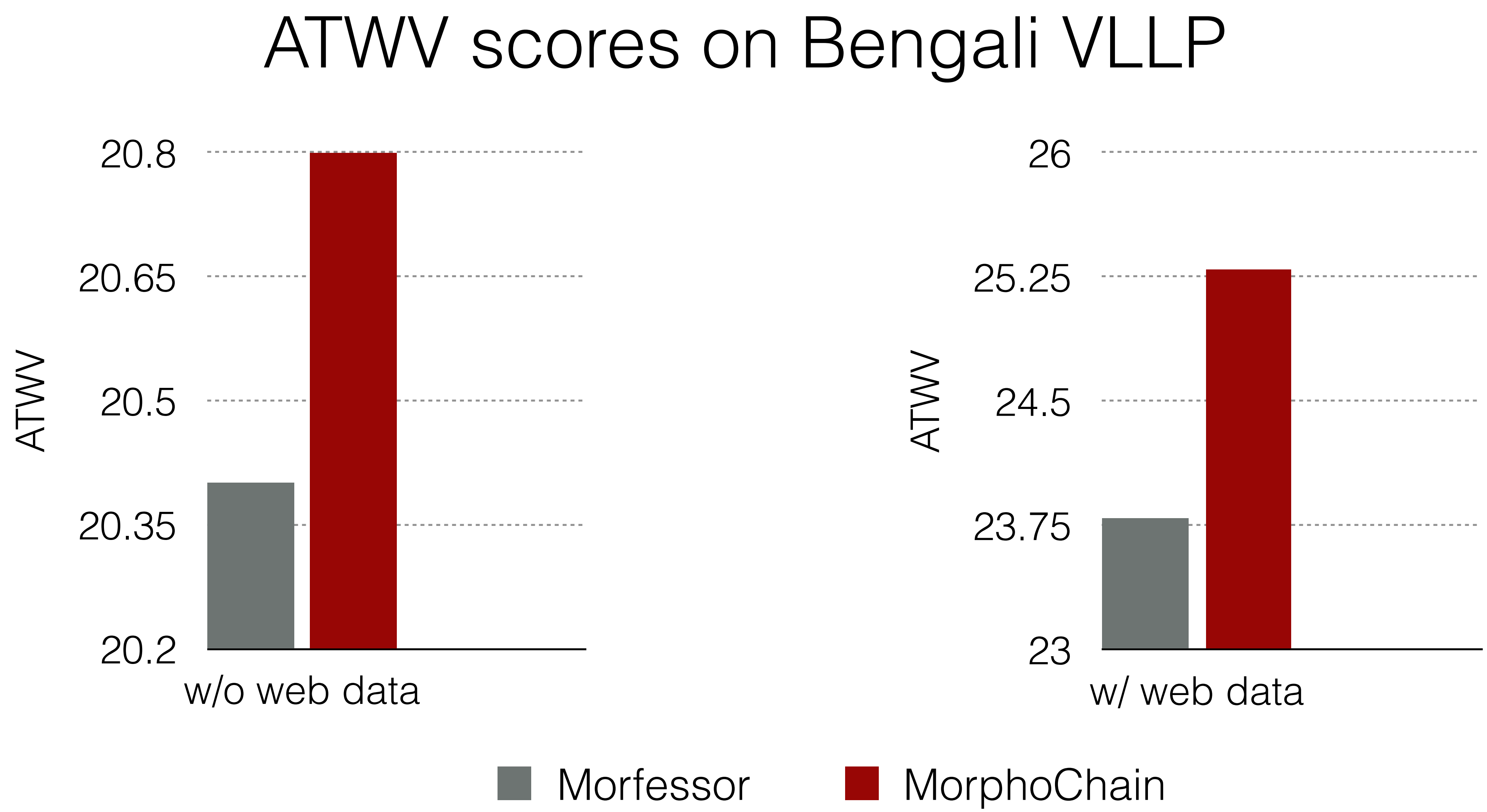


KWS Results on OOV keywords in Turkish LLP (Narasimhan et al., 2014)

- Adding morphemes helps KWS.
- Better morphology can lead to better KWS (supervised vs. unsupervised)
- Need for better unsupervised segmentation.

Morfessor vs MorphoChain for KWS



- MorphoChain outperforms state-of-the-art unsupervised morphological system on KWS

*in collaboration with Damianos Karakos and Rich Schwartz at BBN

Conclusions

- A new method for unsupervised morphological analysis incorporating both orthographic and semantic features.
- Equals or outperforms state-of-the-art systems on morphological segmentation.
- Works well on downstream tasks.

Code: http://people.csail.mit.edu/karthikn/morphochain/