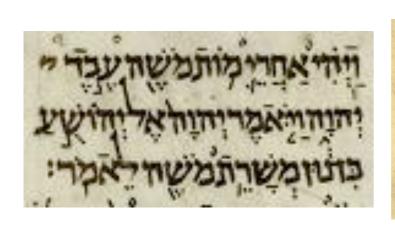
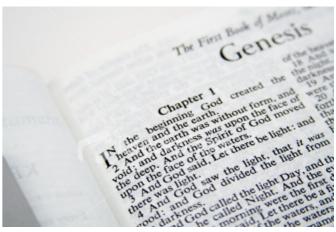
Unsupervised Multilingual Learning for Morphological Segmentation



שות בחובל הובוחה ובשרים האומא שכה מהומה של מה מה בחובל הובוחה ובשרים האומים בל בוחה הוא מותר בל מותר בל בוחה האומים ביל מותר מה המותר בל מותר בל בוחה בל בחוד בל בוחה בל בוחה





Benjamin Snyder and Regina Barzilay
MIT

Unsupervised models for many core tasks proposed

- Unsupervised models for many core tasks proposed
- Performance lags behind supervised models

- Unsupervised models for many core tasks proposed
- Performance lags behind supervised models

How can we cut the unsupervised/supervised performance gap?

Multilingual Learning

Goal:

Induce individual language structures along with interlingual connections with no supervision

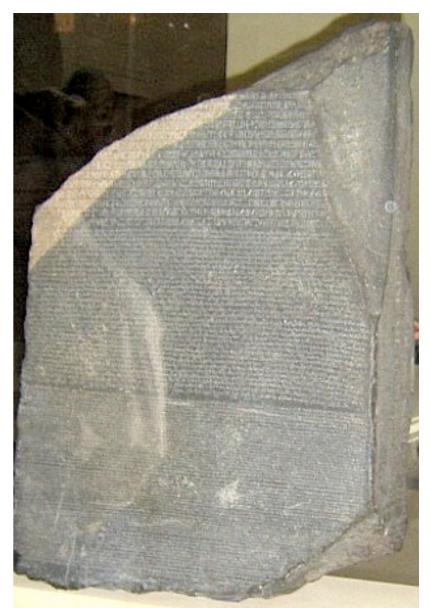
Linguistic Motivation:

- Languages related structurally and historically
- But differ systematically in patterns of ambiguity and expression

Historical Multilingual Learning

- Comparative study of languages goes back to Antiquity
- Achievements:
 - Deciphering unknown scripts
 - Understanding dead languages
 - Reconstructing proto-languages

Use language similarity as bridge Learn from language difference

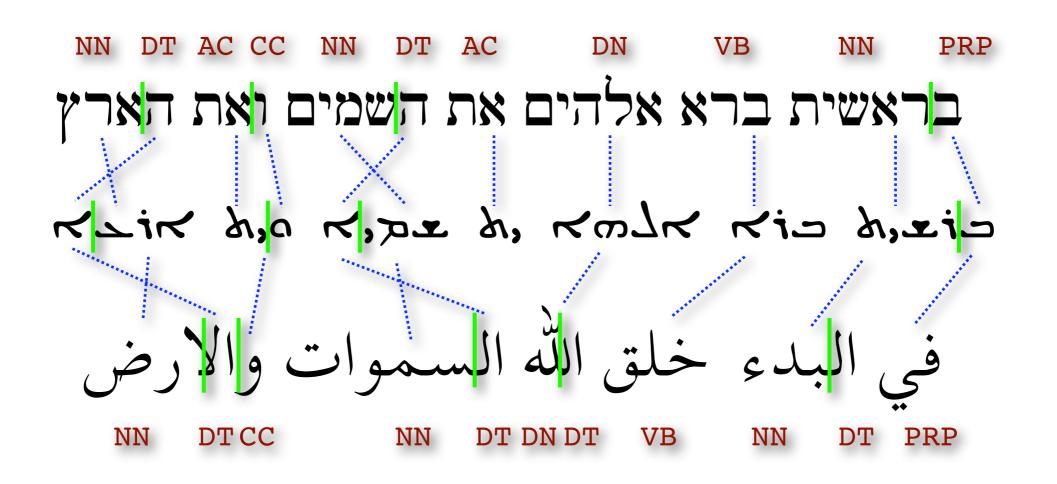


Rosetta Stone

בראשית ברא אלהים את השמים ואת הארץ

בוציא בין איט ארשא אף אבעיא טייף אודא

في البدء خلق الله السموات والأرض





Task: Morphological Segmentation

Input: raw bilingual parallel corpus with no additional resources or knowledge of the languages

Goal: segment each word into smallest units of meaning --- morphemes. e.g.,

fakatabuuhu

so they wrote it

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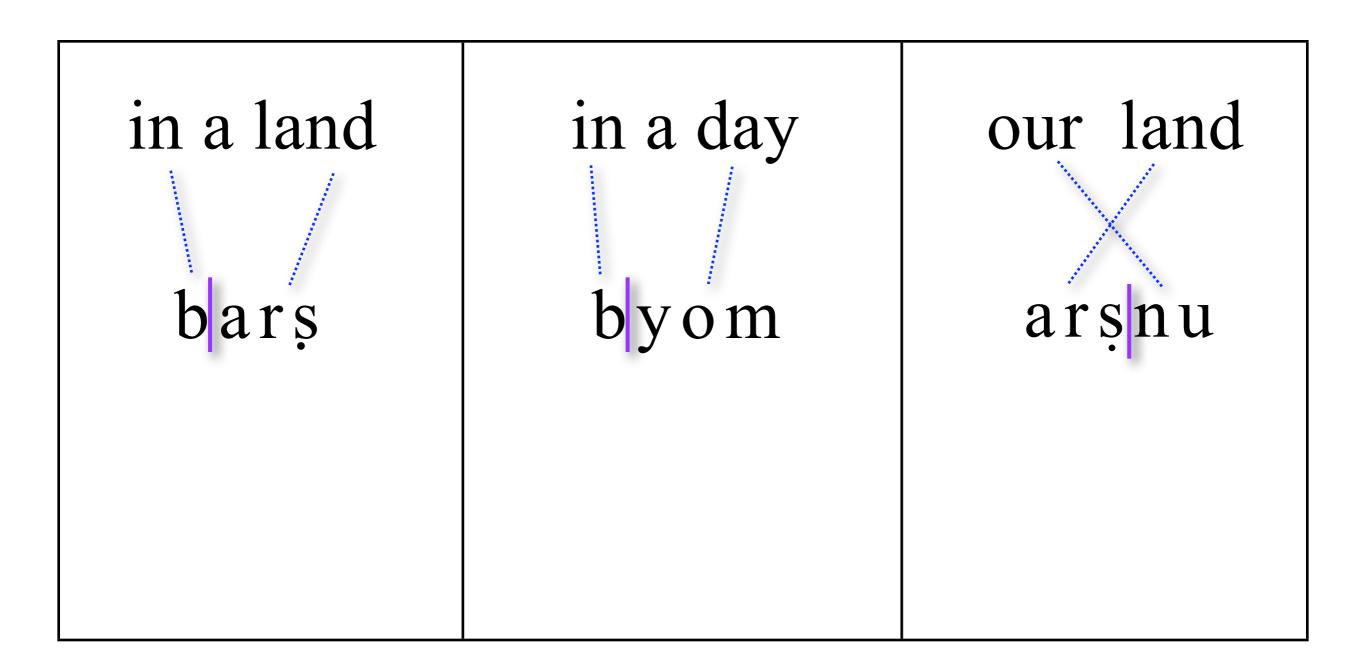
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fakatabuuhu \rightarrow fa katab uu hu so they wrote it \rightarrow so they wrote it

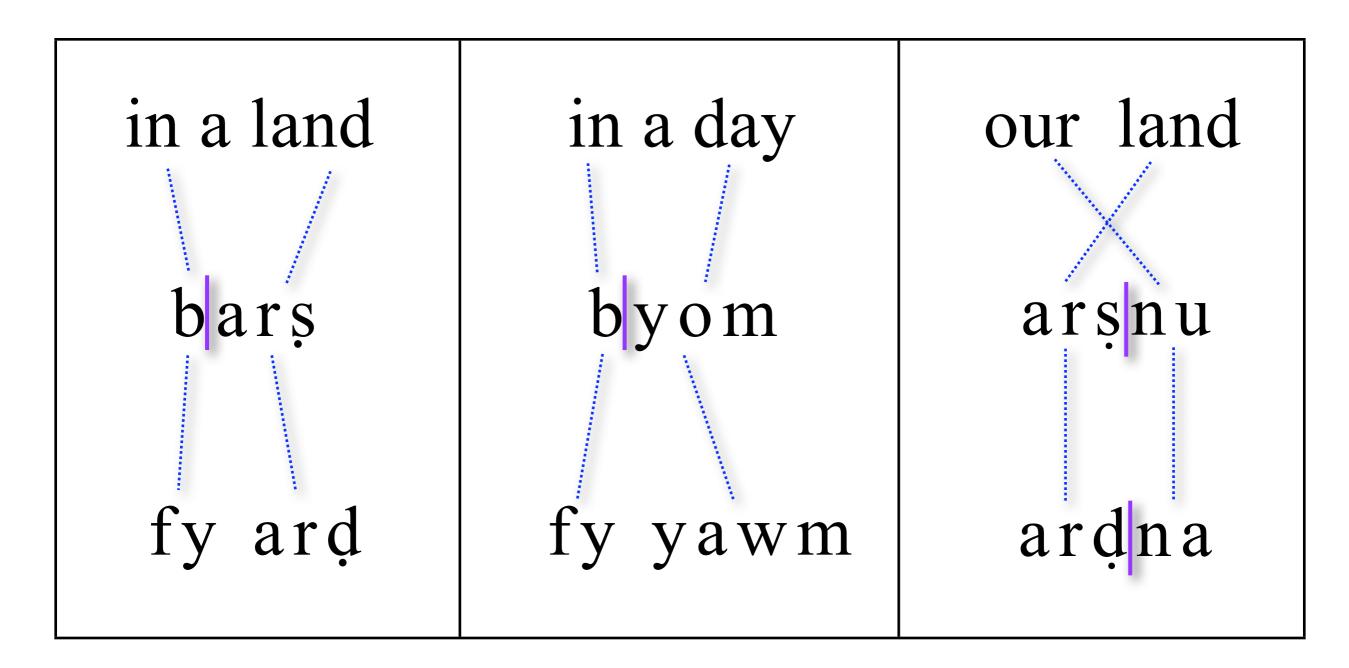
barș	byom	arșnu

in a land	in a day	our land
barș	byom	arșnu

• Learn from different ambiguity patterns



Learn from different ambiguity patterns



- Learn from different ambiguity patterns
- Learn from shared structure
 - ▶ surface similarity (⇒cognates)
 - morpheme inventory

Related Work

 Unsupervised language learning typically formulated in monolingual framework

(Merialdo 1994; Klein 2005; Goldwater 2007)

 Projection of annotations from resourcerich to resource-poor language via parallel corpora

(Yarowsky et al 2000; Xi & Hwa 2005; Klementiev & Roth 2006)

A Generative Approach

Bayesian non-parametric model:

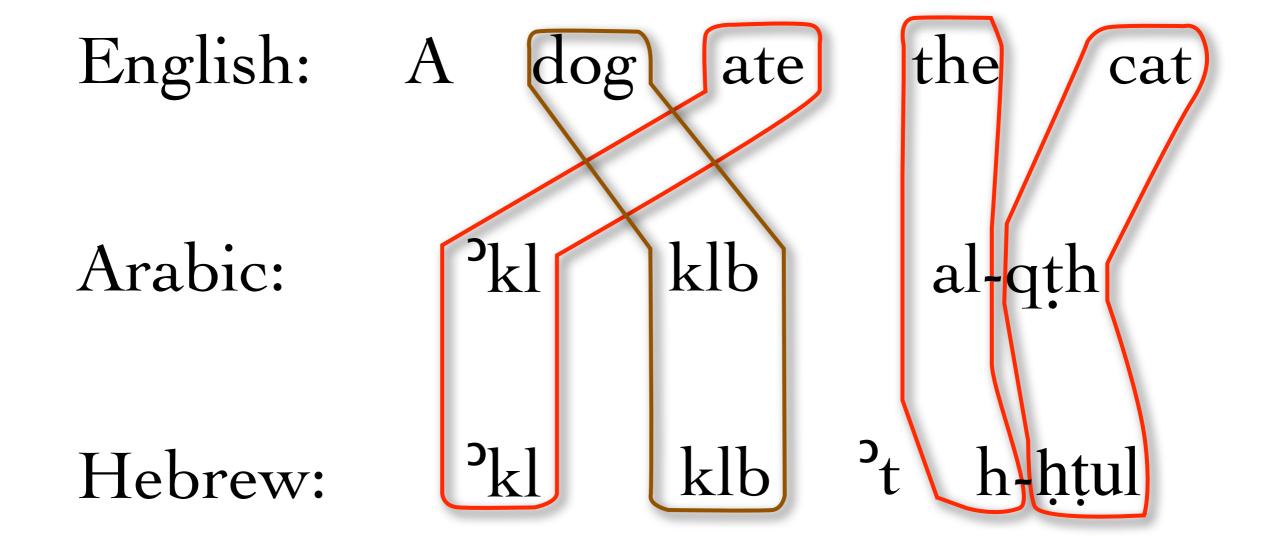
- ▶ Capture multilingual patterns:
 - I. morpheme co-occurrence
 - 2. surface similarity (cognates)
- Allow language-specific idiosyncrasies

<u>Challenge</u>: Jointly model alignments and segmentations

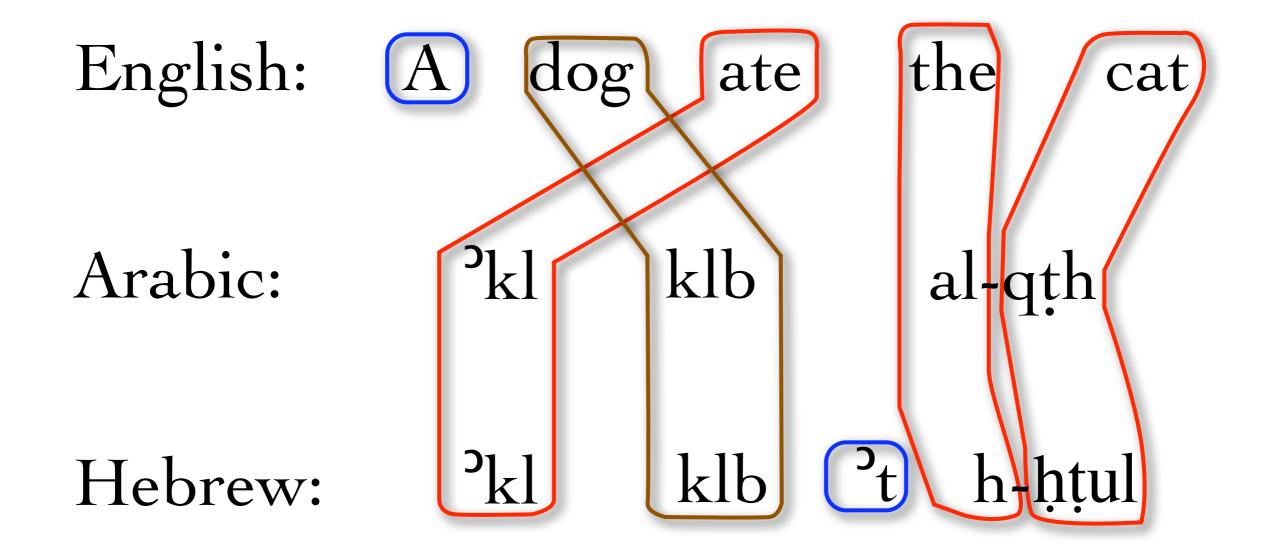
English: A dog ate the cat

Arabic: ³kl klb al-qth

Hebrew: ³kl klb ³t h-htul



Coupled Morphemes: cross-lingual morpheme tuples with common function



Coupled Morphemes: cross-lingual morpheme tuples with common function

Stray Morphemes: morphemes with no analogue in other language

Generative Sketch

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COMPOSE:

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

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GENERATE:

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

²lh god

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

olh god o

⁹hr other

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

In other s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

In other im im god other s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

other s im

ORDER:

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

hr im im other s

ORDER:

²lh

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

od other s

ORDER:

²lh im

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

god other s

ORDER:

olh im ohr

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

god other s

ORDER:

olh im ohr

im

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

Ih im hr im other

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

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Ih im hr im other god

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

The im the im other god s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

FUSE:

Th im hr im other god s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

Ihim hr im other god s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

³lhim ³hrim

other god s

COMPOSE:

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GENERATE:

ORDER:

²lhim

hrim

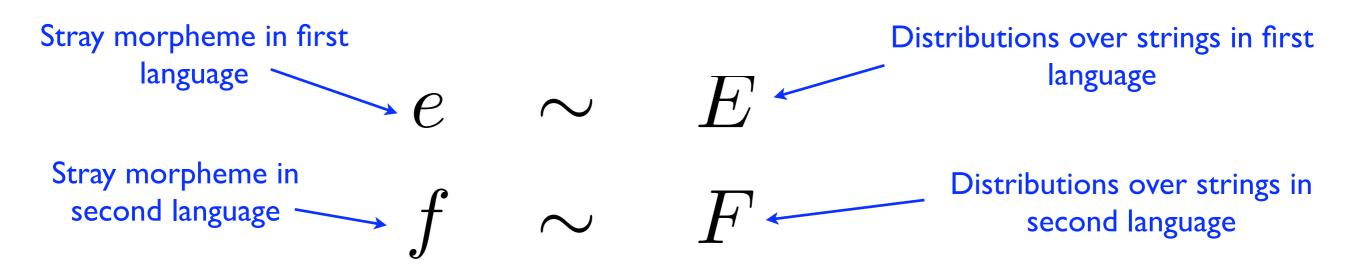
other gods

Morpheme Distributions

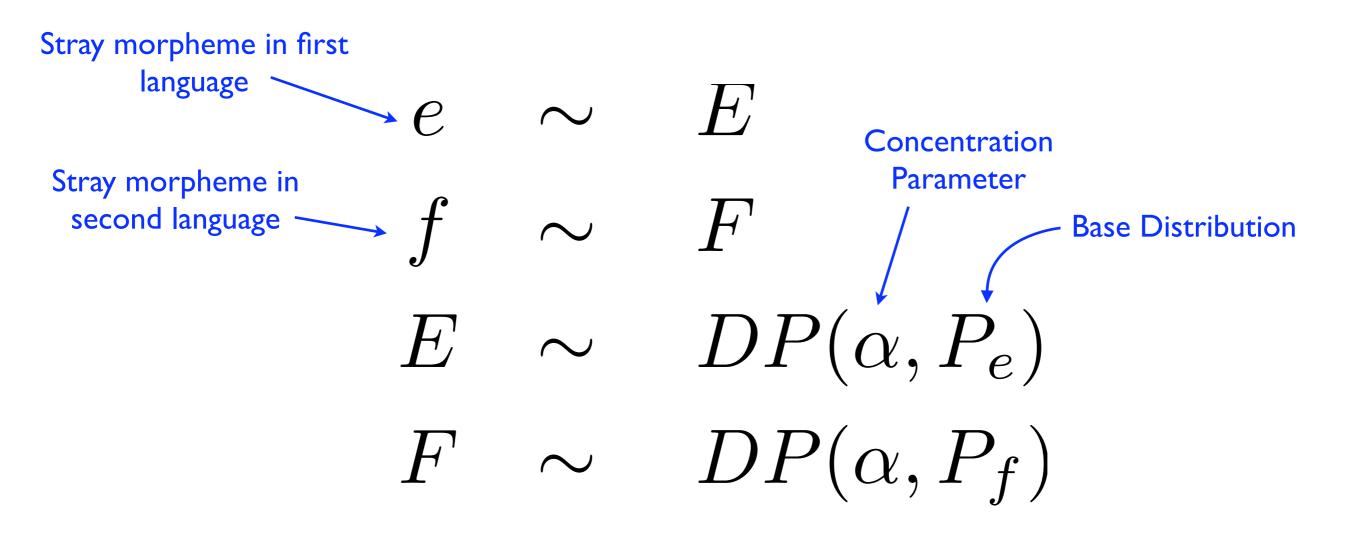
Coupled morpheme distribution:

- Stray morpheme distributions for each language: E, F
- Priors with favorable resulting properties:
 - Infinite
 - Concentrated on few patterns

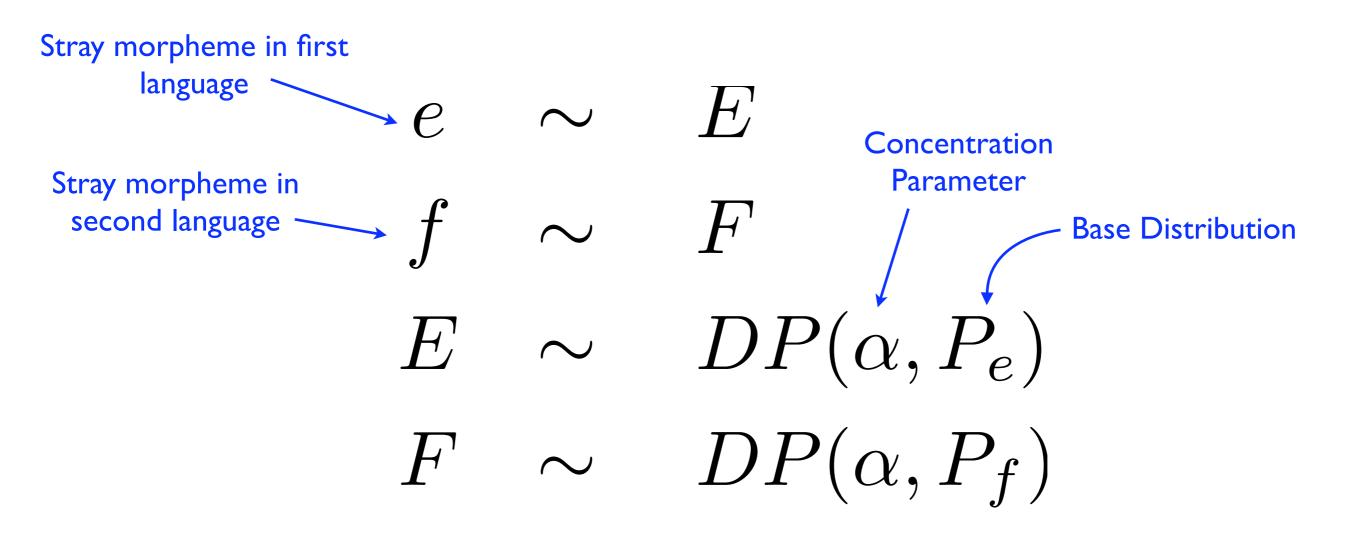
Prior on Stray Morpheme Distributions



Prior on Stray Morpheme Distributions

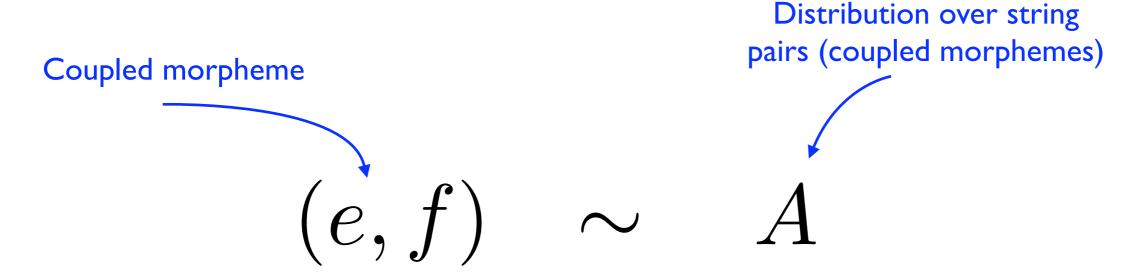


Prior on Stray Morpheme Distributions

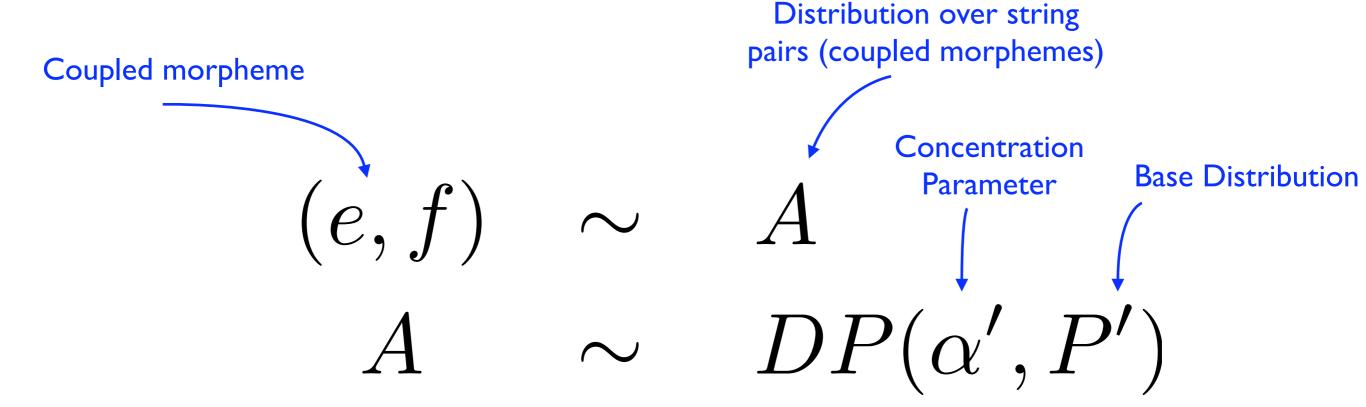


 P_e/P_f : geometric in length of string with special end character

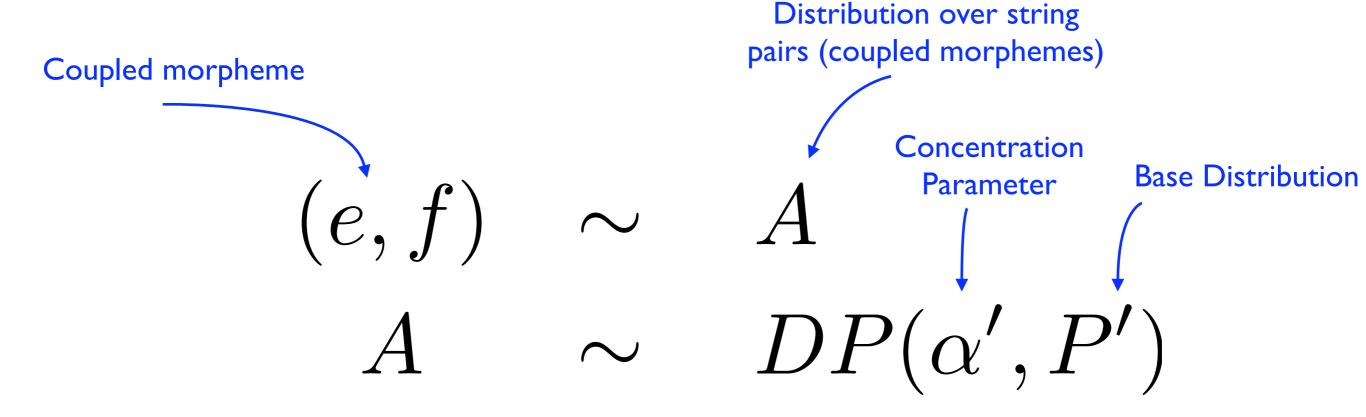
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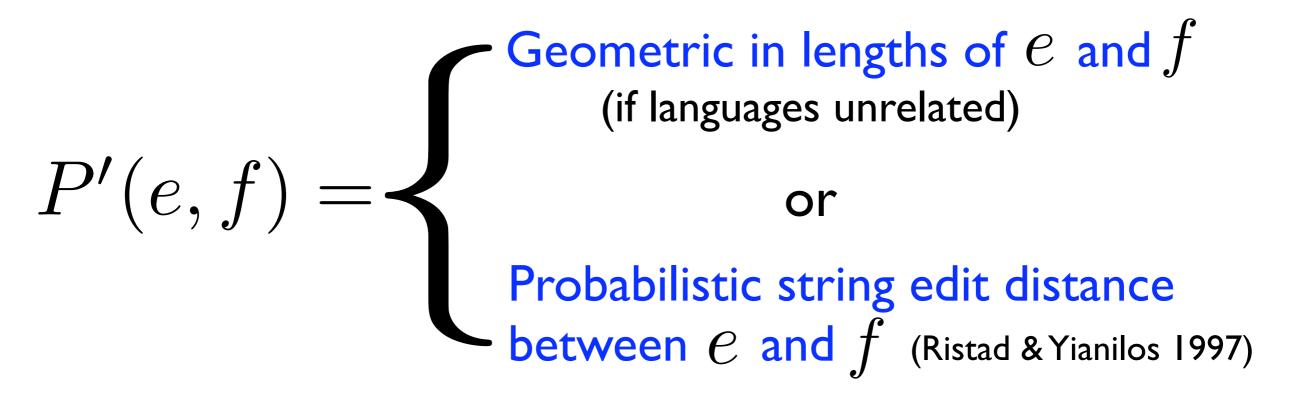


Prior on Coupled Morpheme Distribution



$$P'(e,f)$$
: ???

Exploiting Surface Similarity



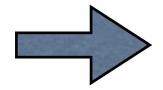
Exploiting Surface Similarity

$$P'(e,f) = \begin{cases} \text{Geometric in lengths of } e \text{ and } f \\ \text{(if languages unrelated)} \end{cases}$$
 or
$$Probabilistic string edit distance between } e \text{ and } f \text{ (Ristad & Yianilos 1997)} \end{cases}$$

Allow substitutions between related letters:

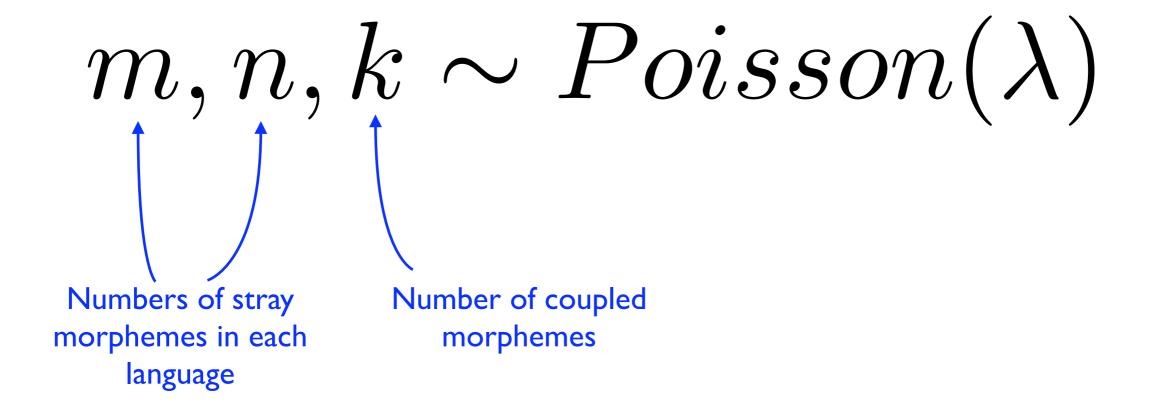
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Choose size and composition of phrase



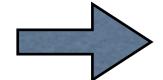
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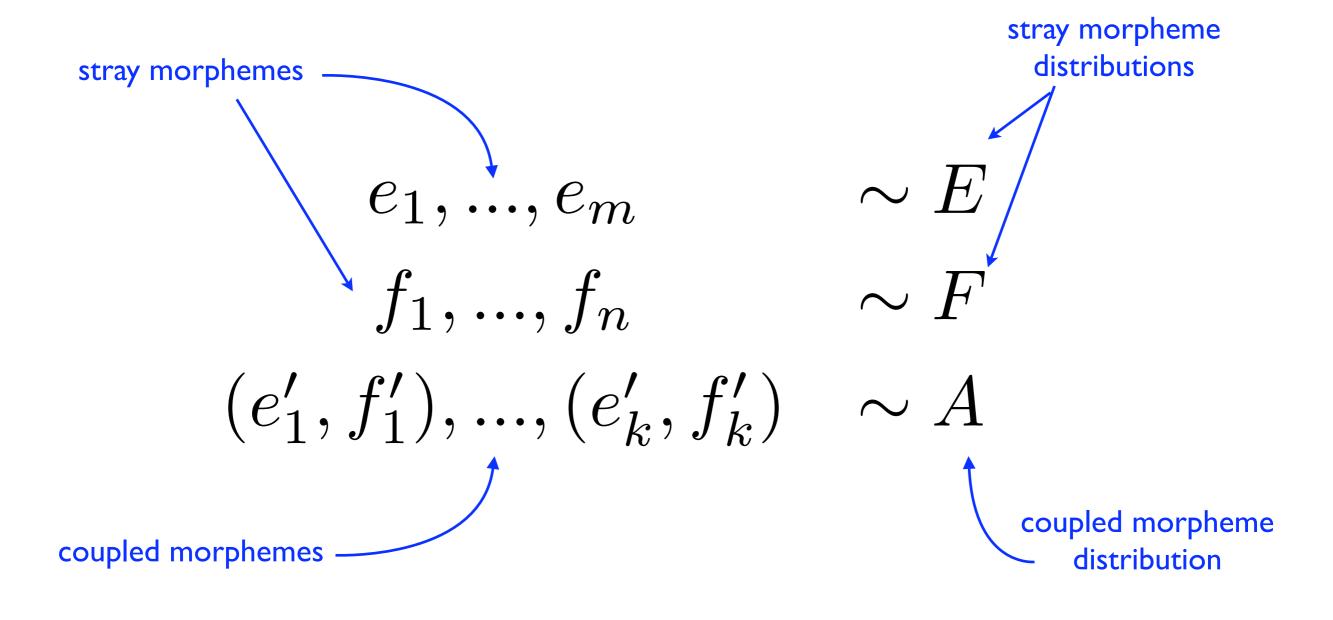
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Generate stray and coupled morphemes



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GENERATE:

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GENERATE:

²lh god

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

olh god o

⁹hr other

COMPOSE:

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GENERATE:

In other s

COMPOSE:

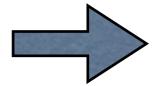
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GENERATE:

In other im im god other s

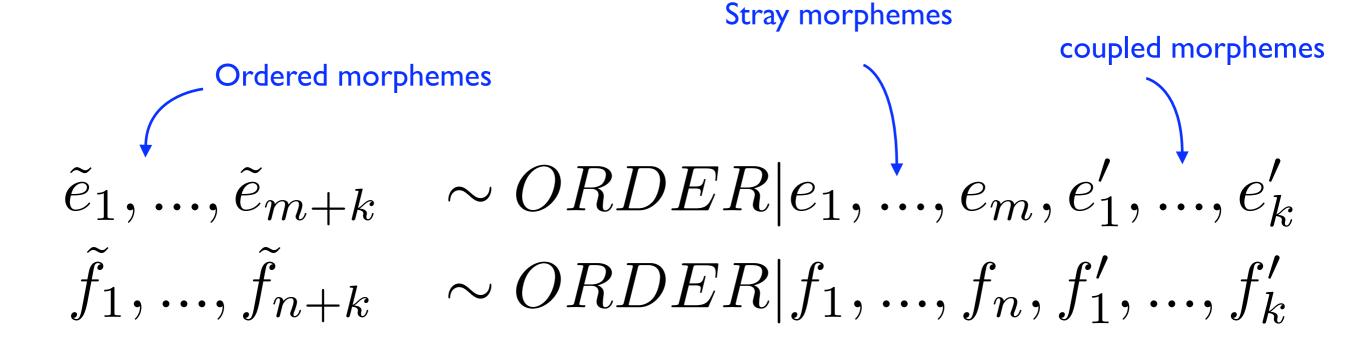
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Order morphemes in each language



Uniform distribution over all possible orderings

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

other s im

ORDER:

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

hr im im other s

ORDER:

²lh

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

hr other s

ORDER:

²lh im

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

god other s

ORDER:

olh im ohr

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

god other s

ORDER:

olh im ohr

im

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

od s

ORDER:

Ih im hr im other

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

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COMPOSE:

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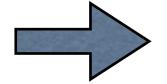
GENERATE:

ORDER:

The im the im other god s

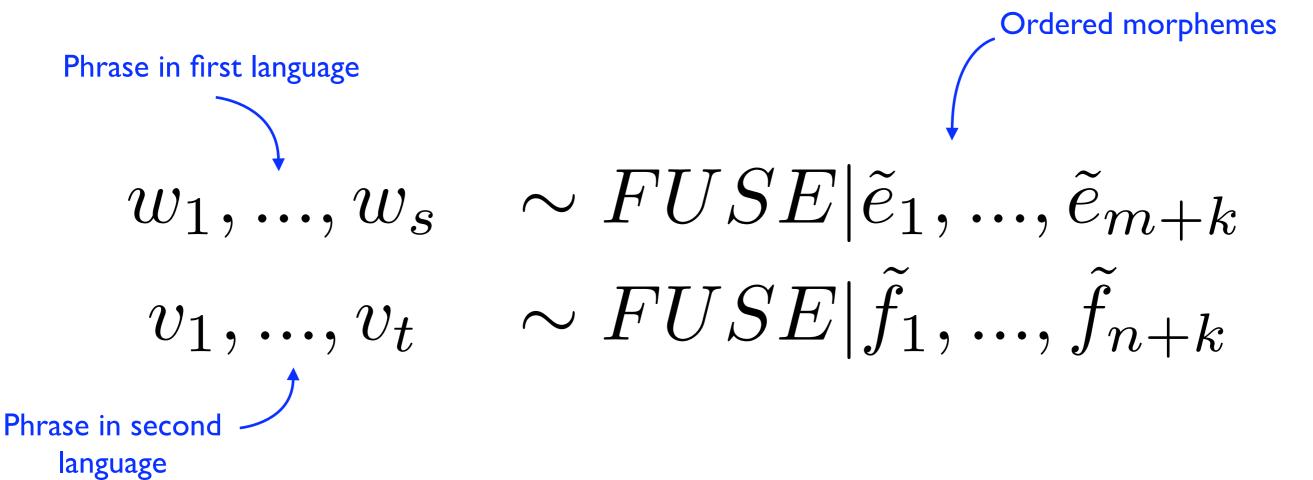
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Fuse ordered morphemes into words



Uniform distribution over all possible fusings

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GENERATE:

ORDER:

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COMPOSE:

three coupled morpheme one stray Hebrew morpheme

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ORDER:

Thim hr im other god s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

Thim hrim other god s

COMPOSE:

three coupled morpheme one stray Hebrew morpheme

GENERATE:

ORDER:

other gods

Gibbs Sampling

- Use standard closed forms (CRP)
- Integrate over
 - "Parameters": coupled and stray morpheme distributions θ
 - lacktriangleright Hidden variables: identity of stray and coupled morphemes in each phrase \mathcal{Z}
- Produce segmentations with highest posterior likelihood:

$$\underset{y}{\operatorname{argmax}} P(y|x) = \underset{y}{\operatorname{argmax}} \int_{\theta} \int_{z} P(y, x, z, \theta) \, dz \, d\theta$$

Data

- Bible: Hebrew, Aramaic, Arabic, English
- 6,139 short parallel phrases automatically extracted
- Words per phrase: I 6
- Gold Standard:
 - Hebrew: Westminster Theological Seminary
 - ► Arabic: MADA (Buckwalter; Habash & Rambow 2005)
 - Morphemes per word: 1.8

Evaluation

- Evaluate on separate Monolingual test data
- Examine all possible segmentation points:

Calculate precision, recall, and F-measure

Results for Arabic (similar for Hebrew)

Morphological Segmentation: Baselines

	F-Measure
Random	18.8
Morfessor (Creutz & Lagus '05)	65.4
Monolingual Baseline	63.2

Morfessor:

State-of-the-art unsupervised (monolingual) model

Monolingual Baseline:

Train a single language with stray morpheme distribution (similar to (Goldwater 2007))

	F-Measure
Monolingual Baseline	63.2
Arabic+Hebrew	
Arabic+Aramaic	
Arabic+English	
Arabic+Aramaic (String-edit)	
Arabic+Hebrew (String-edit)	

	F-Measure
Monolingual Baseline	63.2
Arabic+Hebrew	68.3
Arabic+Aramaic	68.6
Arabic+English	
Arabic+Aramaic (String-edit)	
Arabic+Hebrew (String-edit)	

▶ Multilingual learning effective

	F-Measure
Monolingual Baseline	63.2
Arabic+Hebrew	68.3
Arabic+Aramaic	68.6
Arabic+English	68.5
Arabic+Aramaic (String-edit)	
Arabic+Hebrew (String-edit)	

- ▶ Multilingual learning effective
- ▶ English equally effective

	F-Measure		
Monolingual Baseline	63.2		
Arabic+Hebrew	68.3		
Arabic+Aramaic	68.6		
Arabic+English	68.5		
Arabic+Aramaic (String-edit)	70.8		
Arabic+Hebrew (String-edit)	72.2		

- Multilingual learning effective
- English equally effective
- Best result with related languages using string-edit prior (cognates)

Conclusions

Multilingual Learning: a new approach to unsupervised learning

- Simultaneously induce linguistic structure with interlingual links
- Exploit different patterns of ambiguity while finding shared structure

Key findings:

- Error reduction up to 24% for morphological segmentation
- Best results: learning within language family with string-edit prior (cognates)

Future work:

- Apply to many languages simultaneously
- Apply to other core NLP tasks

Can we exploit cross-lingual patterns to improve unsupervised language learning?

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√ morphological segmentation error reduction of 24%

Will joint analysis provide more or less benefit when the languages belong to the same family?

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 Unrelated but "easier" languages provide large benefit.

Will joint analysis provide more or less benefit when the languages belong to the same family?

- Unrelated but "easier" languages provide large benefit.
- Best performance: within-family learning when surface similarity used.

Thank You!

For supervised results see:

Benjamin Snyder & Regina Barzilay. Cross-lingual Propagation for Morphological Analysis. AAAI 2008

http://people.csail.mit.edu/bsnyder

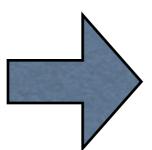
Morphological Segmentation

"In my land"

• Hebrew: barsy

• Arabic: fy ardy

• Aramaic: barsy



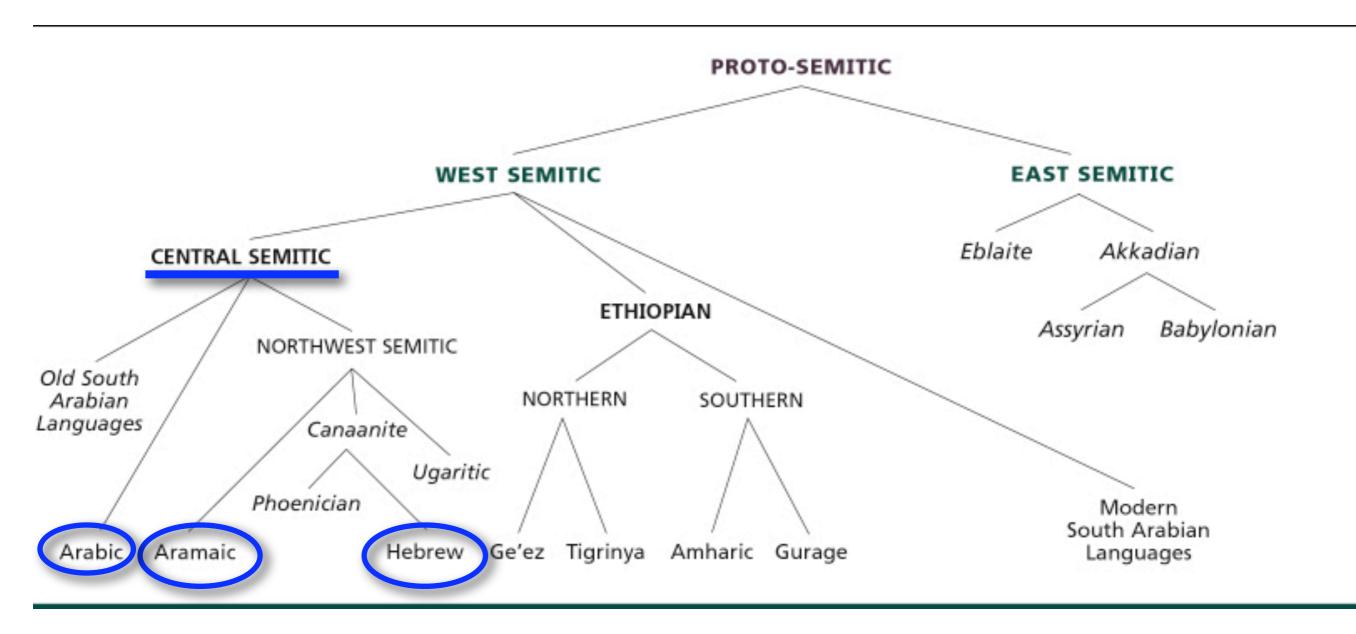
"In" "land" "my"

•
$$b - ars - y$$

• $fy \ ard - y$

• $b - ars - y$

Semitic Languages



Related Work

 Unsupervised language learning typically formulated in monolingual framework

(Merialdo 1994; Klein 2005; Goldwater 2007)

 Projection of annotations from resourcerich to resource-poor language via parallel corpora

(Yarowsky et al 2000; Xi & Hwa 2005; Klementiev & Roth 2006)

Generative Outline

Draw parameters from priors:

 $\theta \sim P(\theta)$

Generate hidden structure from parameters:

$$z \sim P(z|\theta)$$

 Produce bilingual parallel phrases from hidden structure:

$$x \sim P(x|z)$$

"Read off" segmentation

$$x, z \Rightarrow y$$

In the beginning God created the heavens and the earth.

בראשית ברא אלהים את השמים ואת הארץ

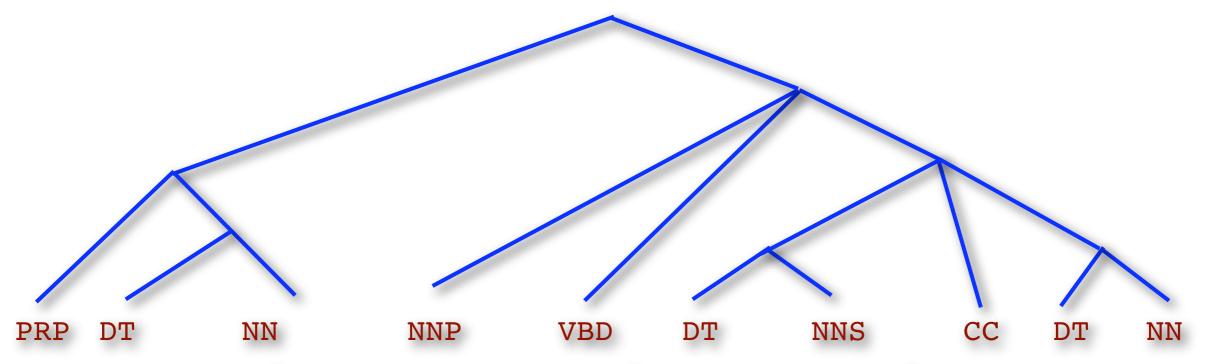
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PRP DT NN NNP VBD DT NNS CC DT NN

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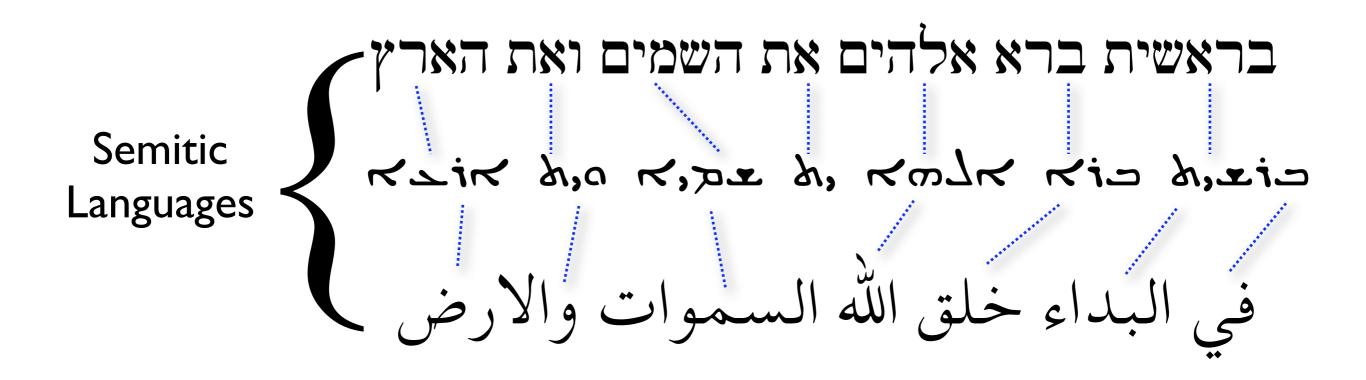
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Multilingual Corpora: A Rosetta Stone for unsupervised NLP

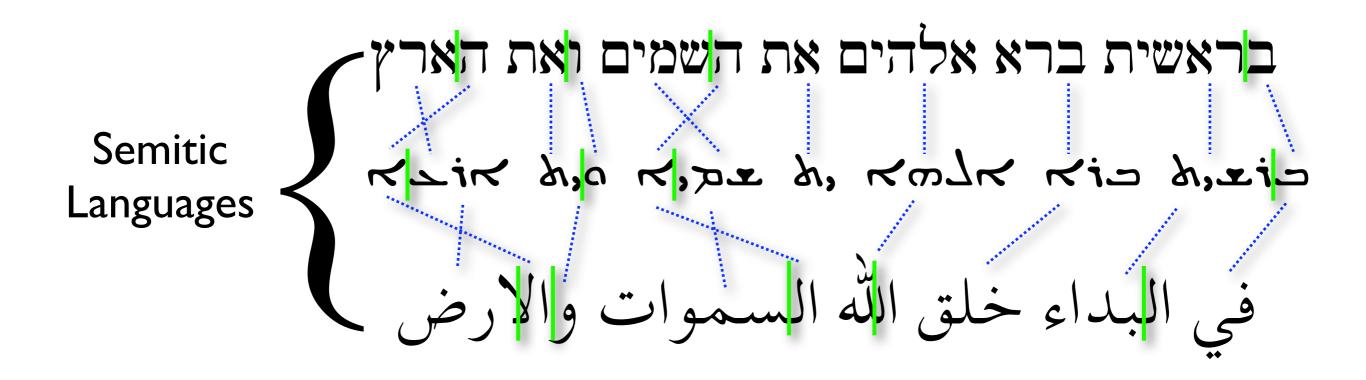
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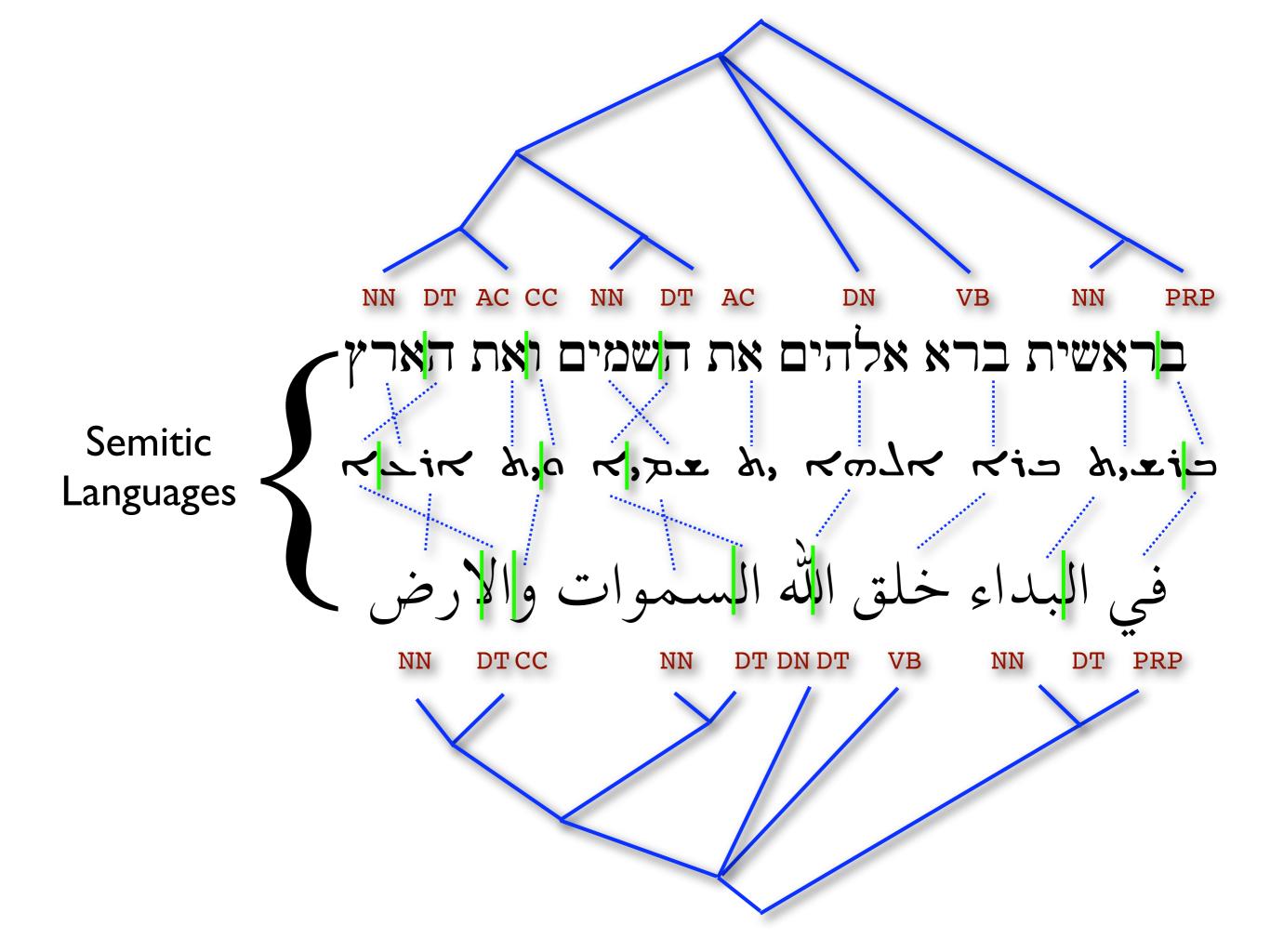


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حادی الله السموات والارض