Phonetic and Visual Priors for Decipherment of Informal Romanization

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Language Technologies Institute

ML
MACHINE LEARNING
DEPARTMENT

UCSDCSE
Computer Science and Engineering

In a Nutshell…

- Decoding transliteration in social media
- Inductive bias: character similarity
- Unsupervised finite-state approach
- New dataset of romanized Russian
- Performance on par with supervised!

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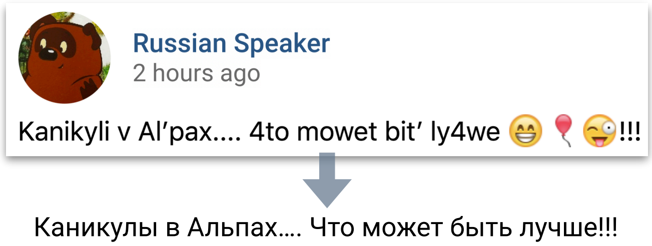

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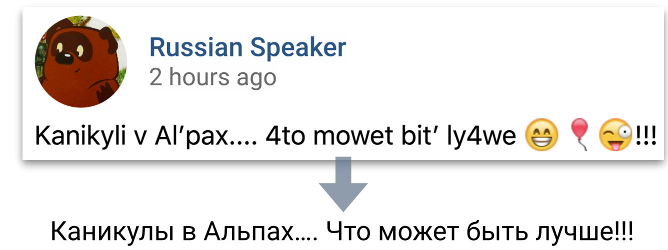

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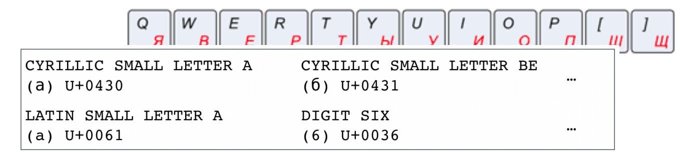

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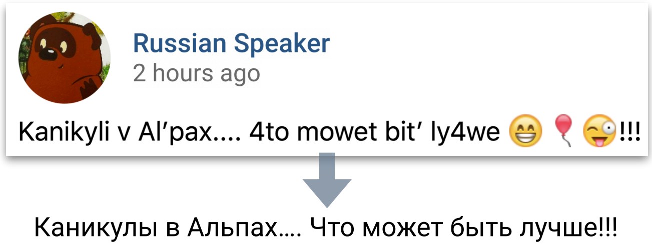

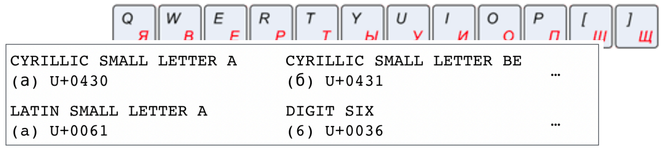

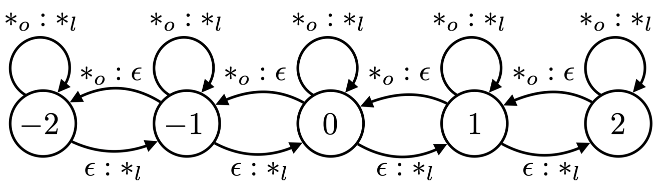

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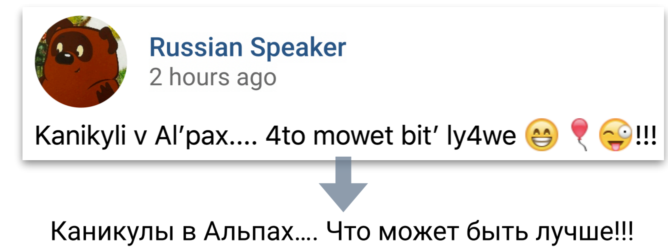

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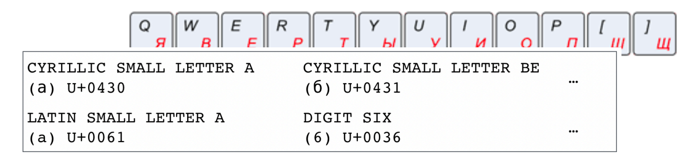

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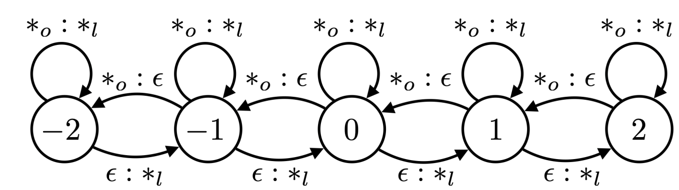

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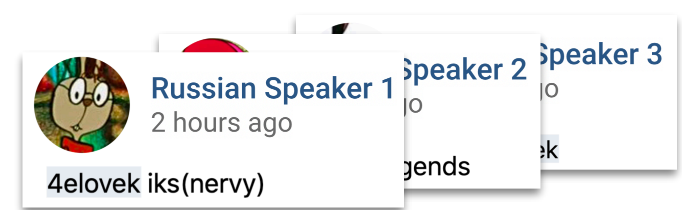

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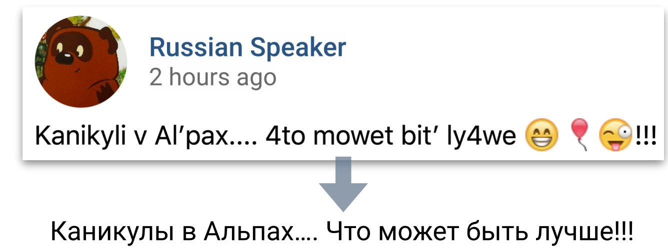

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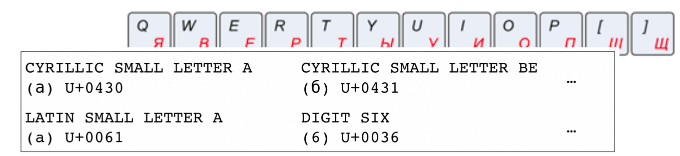

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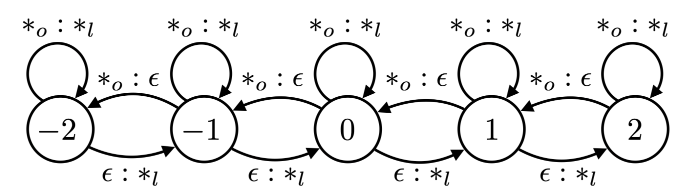

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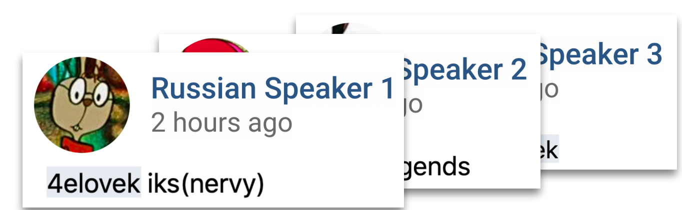

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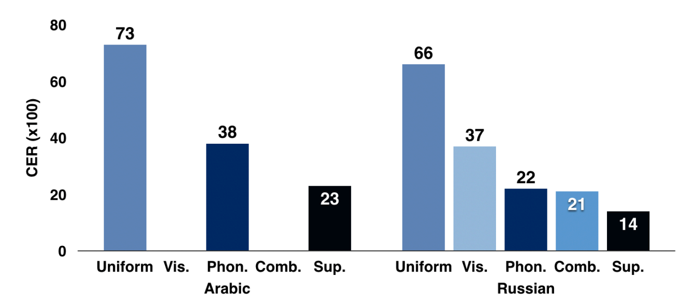

Informal Romanization

Russian Speaker
2 hours ago

Kanikyli v Al’pax.... 4to mowet bit’ ly4we 😁 🎈 😜!!!

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What they type (Latin):	`Kanikyli v Al’pax`
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goal

Visual and Phonetic Patterns

- Some character substitutions are phonetic…

Latin:	Kanikyli v Al’pax
Cyrillic:	Каникулы в Альпах
	/n/ /p/

+ Arabic ش /ʃ/ → **sh**, Russian **м /m/** → **m**, etc.

Visual and Phonetic Patterns

- Some character substitutions are phonetic…
- …and some are visual

Latin:	Kanikyli v Al’pax
Cyrillic:	Каникулы в Альпах
	/u/ /x/

+ Arabic ع /ʕ/ → 3, Russian в /v/ → B, etc.

Visual and Phonetic Patterns

- Some character substitutions are phonetic…
- …and some are visual
- It is a many-to-many cipher that also varies across users

Latin:	`Kanikyli v Al'pax`
Cyrillic:	`Каникулы в Альпах`
	/i/ /ɨ/

+ Arabic ص → s ← س, Russian 8 ← в → B, etc.

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- **Hypothesis**: inductive bias encoding these similarity notions provides signal that can approximate human supervision

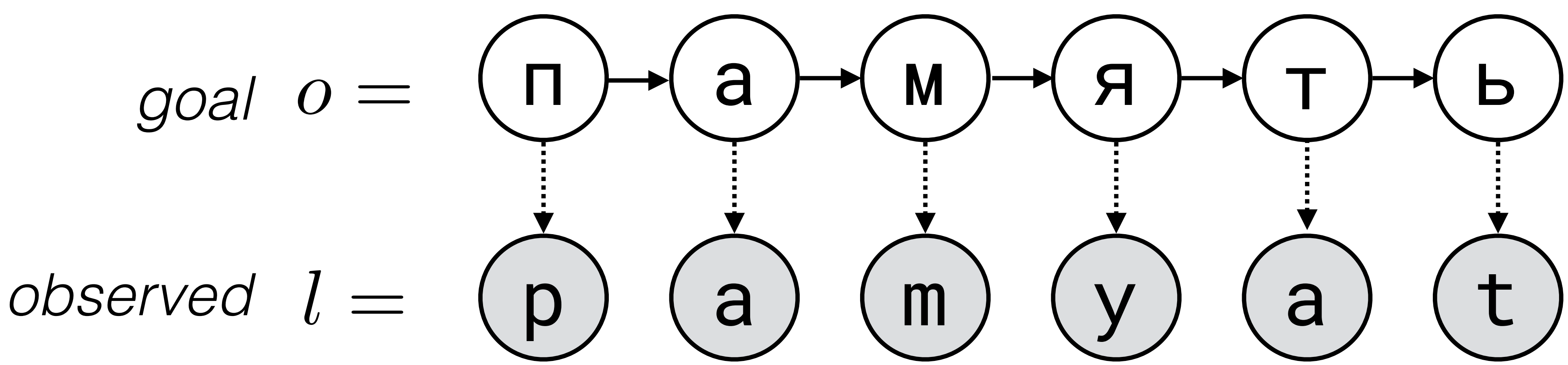
Noisy Channel Model

$$p(l) = \sum_{o} p(o;\gamma) \cdot p(l|o;\theta) \cdot p_{\text{prior}}(\theta;\alpha)$$

transition probabilities

emission probabilities

prior on parameters



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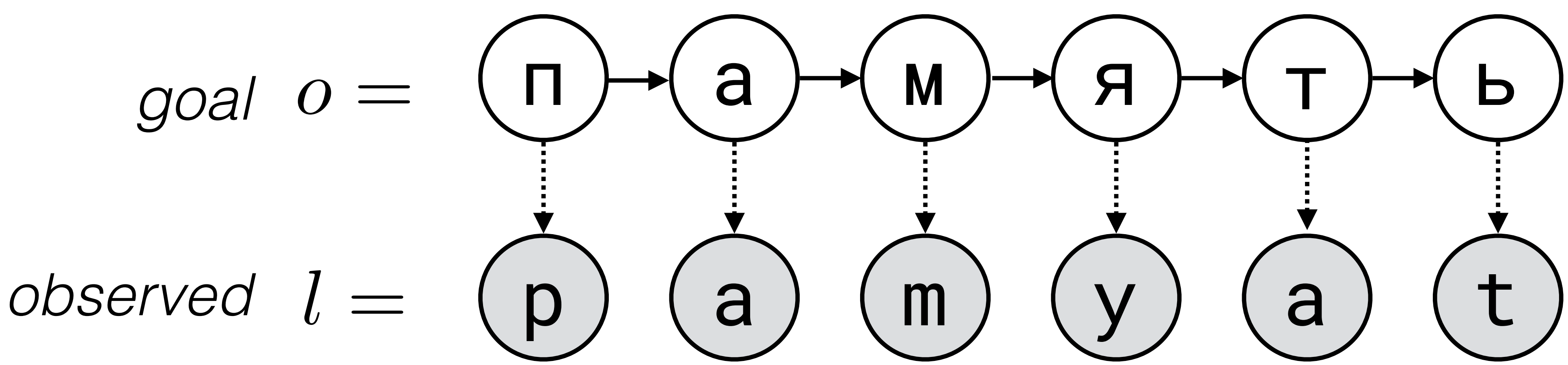

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- Visual prior: read mappings off Unicode confusable symbols list

CYRILLIC SMALL LETTER A (а) U+0430	CYRILLIC SMALL LETTER BE (б) U+0431	…
LATIN SMALL LETTER A (a) U+0061	DIGIT SIX (6) U+0036	…

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acl2020.org → ACL 2020
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асl2020.org → ???
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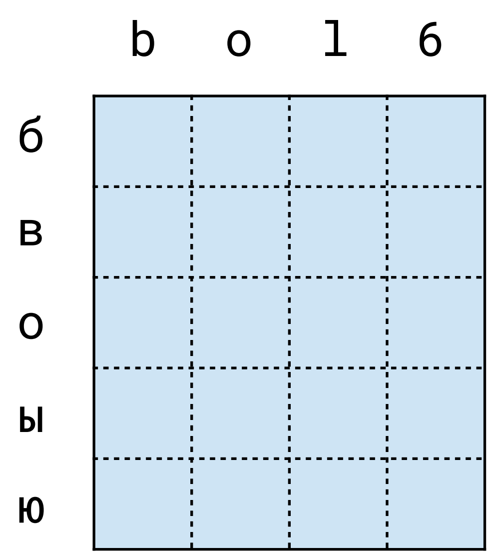
  - No Arabic—Latin mappings due to script dissimilarity

Inductive Bias

- Use mappings of similar characters as priors on emission parameters

$$c_l | c_o \sim \mathrm{Mult}(\theta_{c_o}) \qquad \theta \sim \mathrm{Dir}(\alpha)$$



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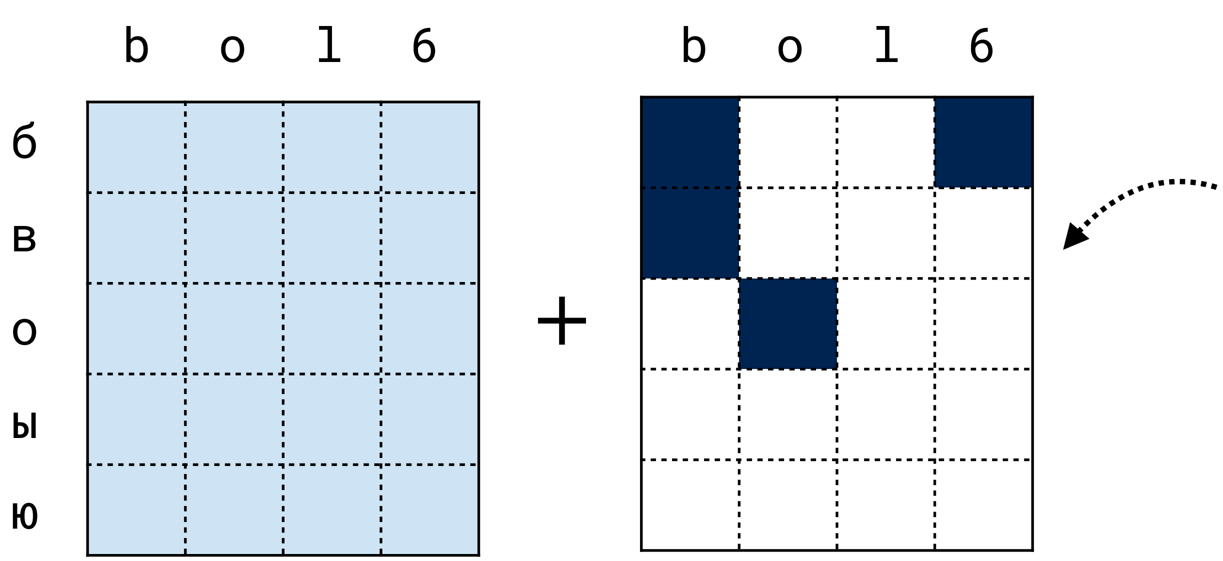

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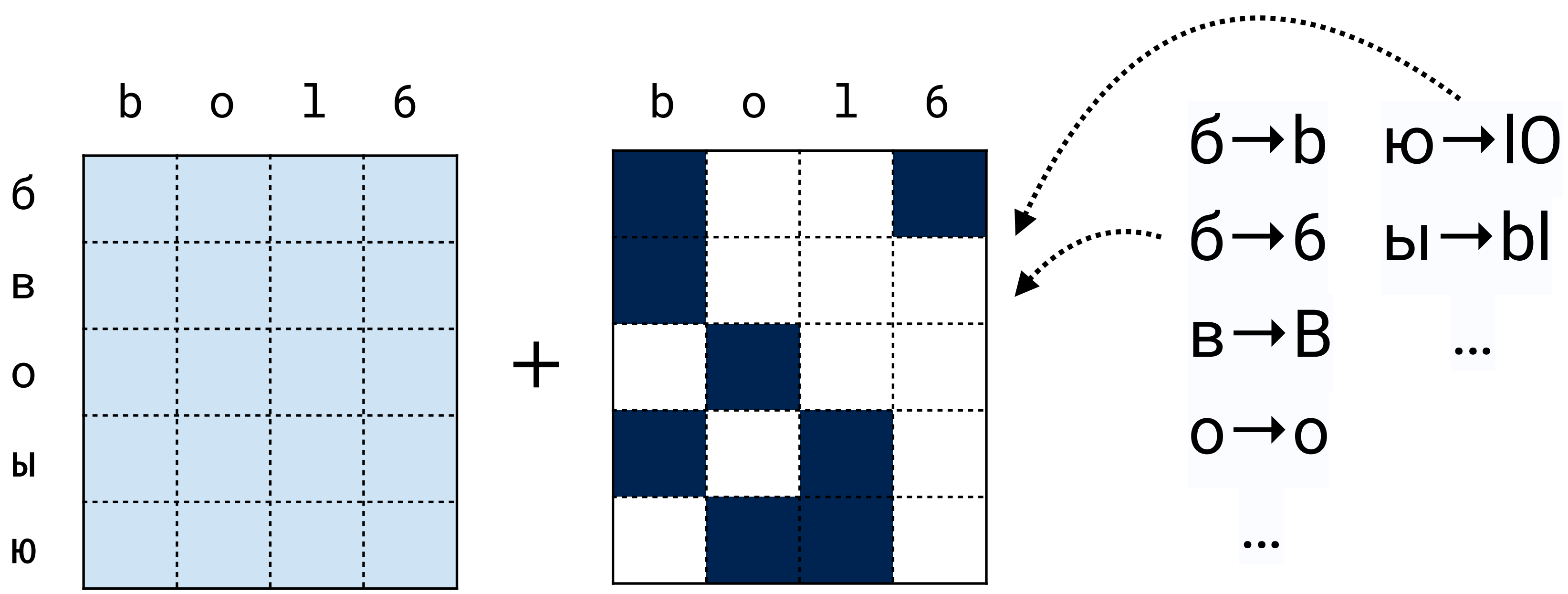

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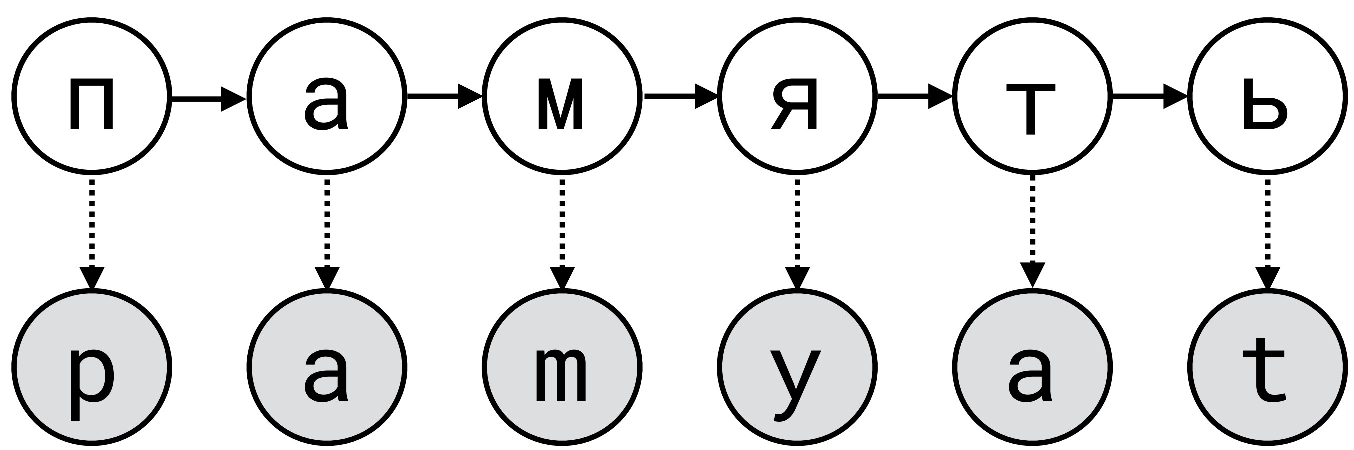
goal $o =$

observed $l =$



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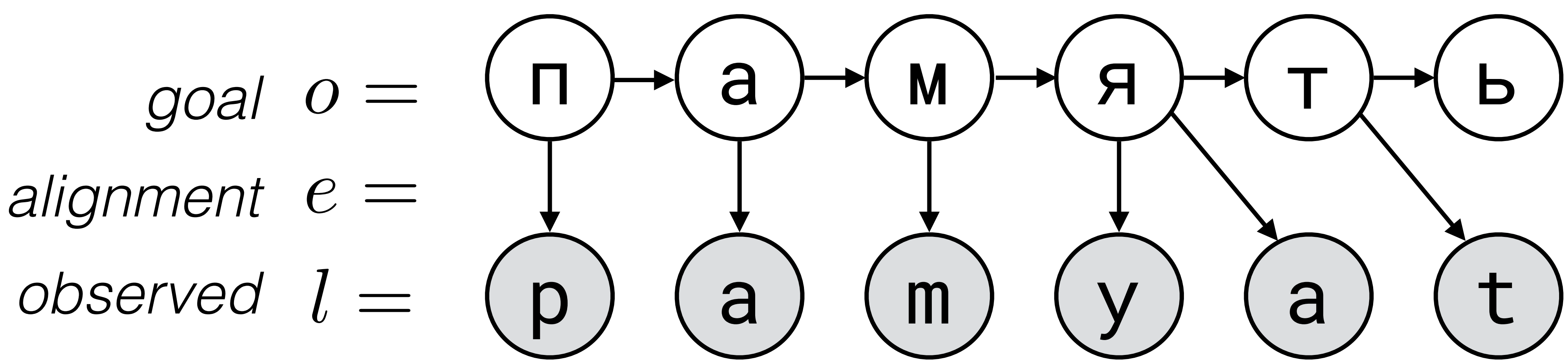

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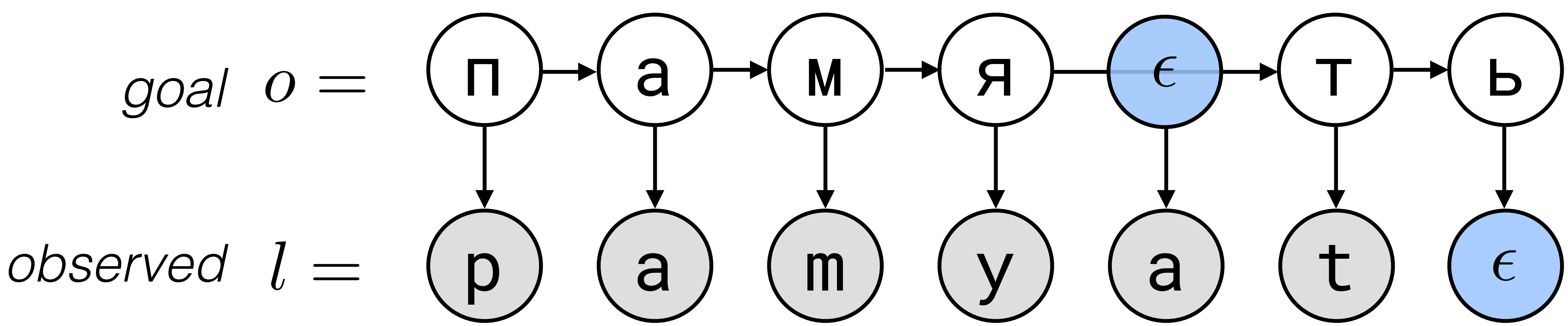
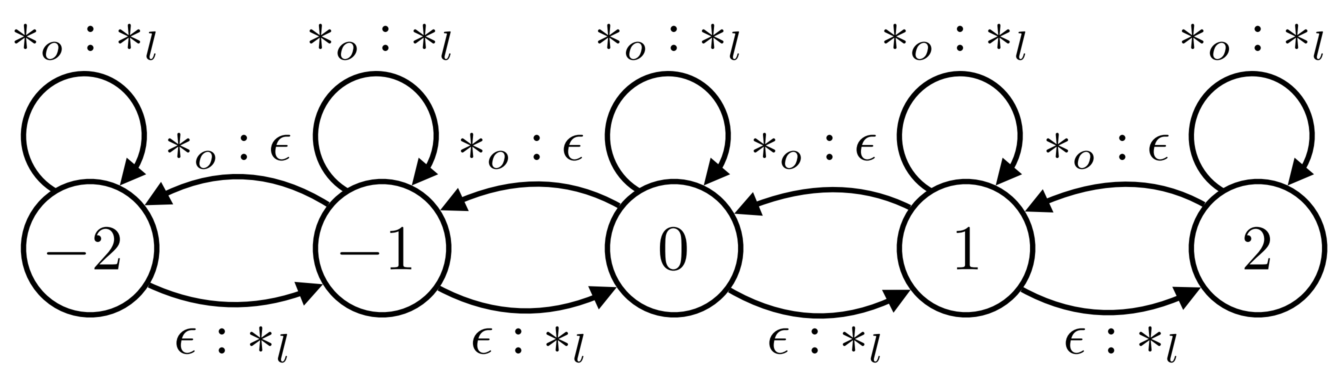


Representing latent alignment via insertions and deletions

WFST Cascade

- Transition model: original script n-gram LM
- Emission model: WFST supporting deletions and insertions, with limited <u>delay</u>



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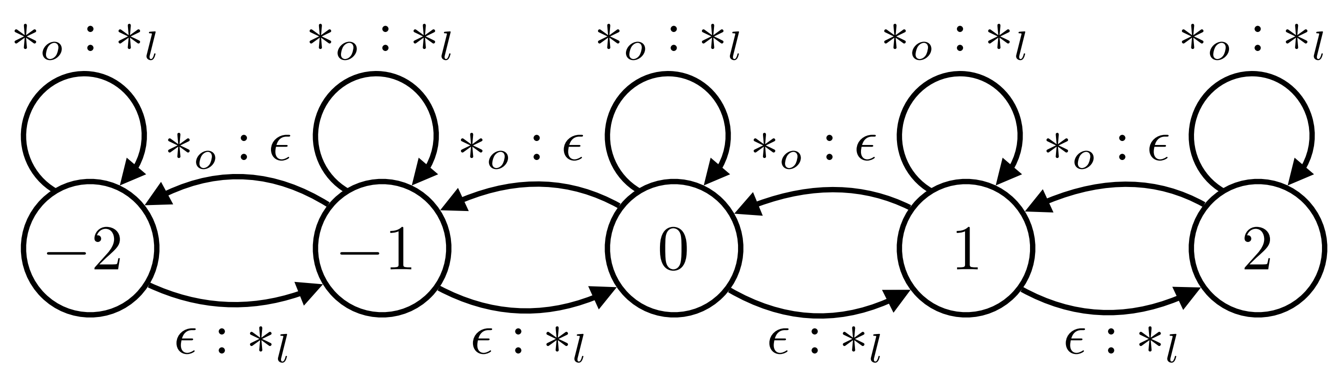

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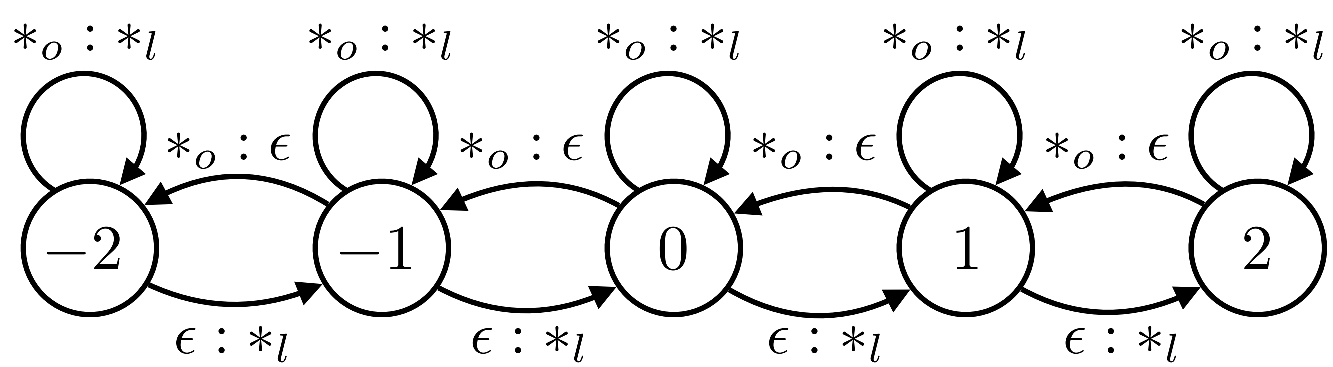

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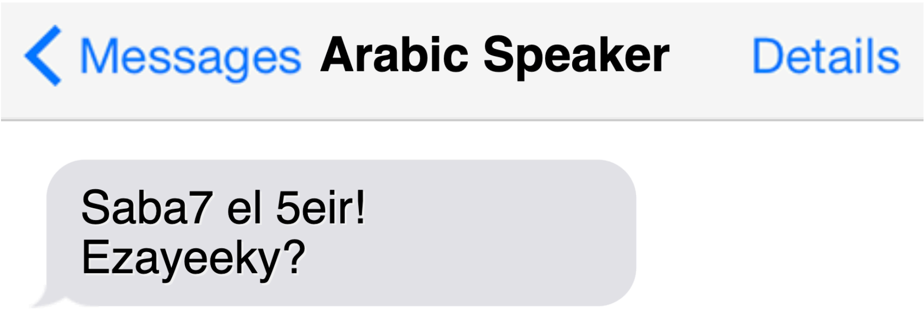
- Trained with EM algorithm + stepwise training, curriculum learning, pruning…

Data

- Arabic: LDC BOLT dataset (SMS / chat dialogs)



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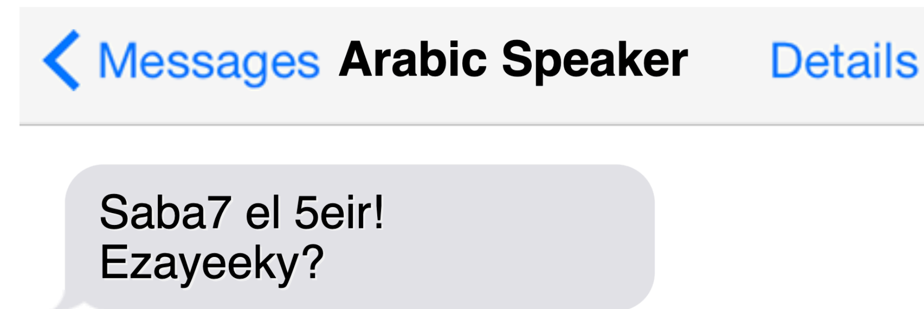

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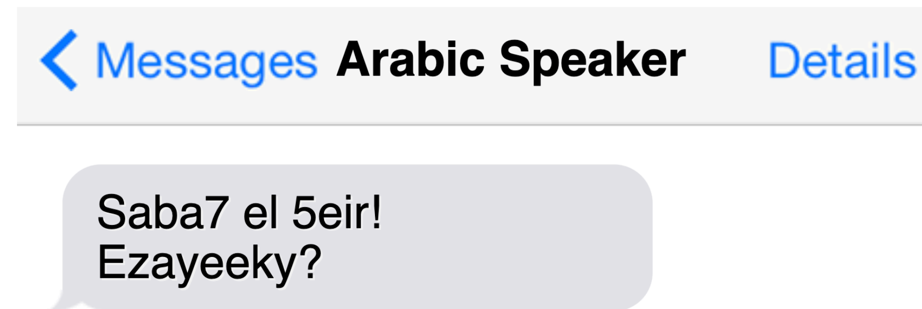

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человек → 4elovek, chelovec, 4eJloBek, …

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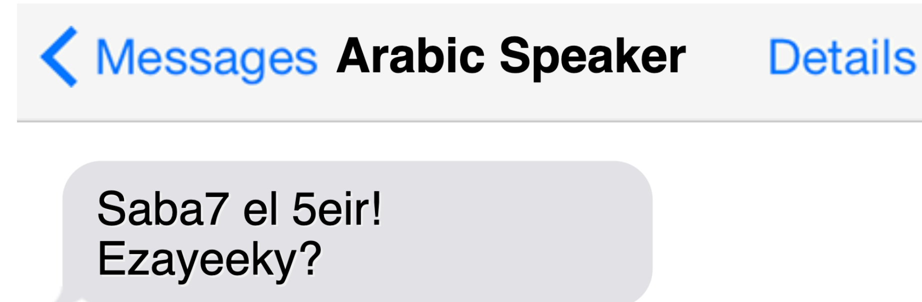

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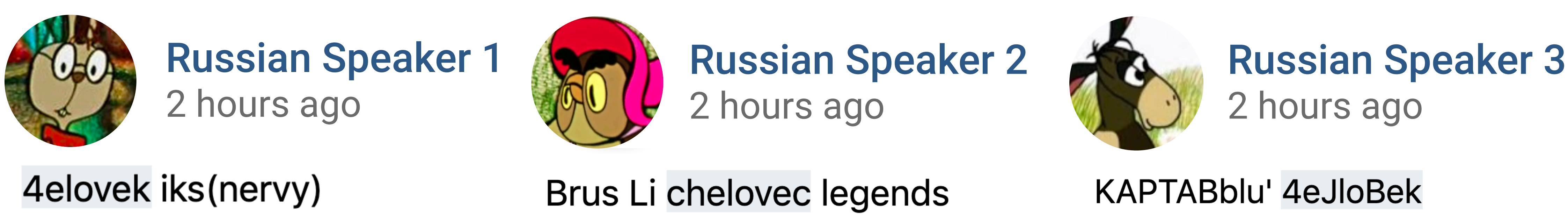

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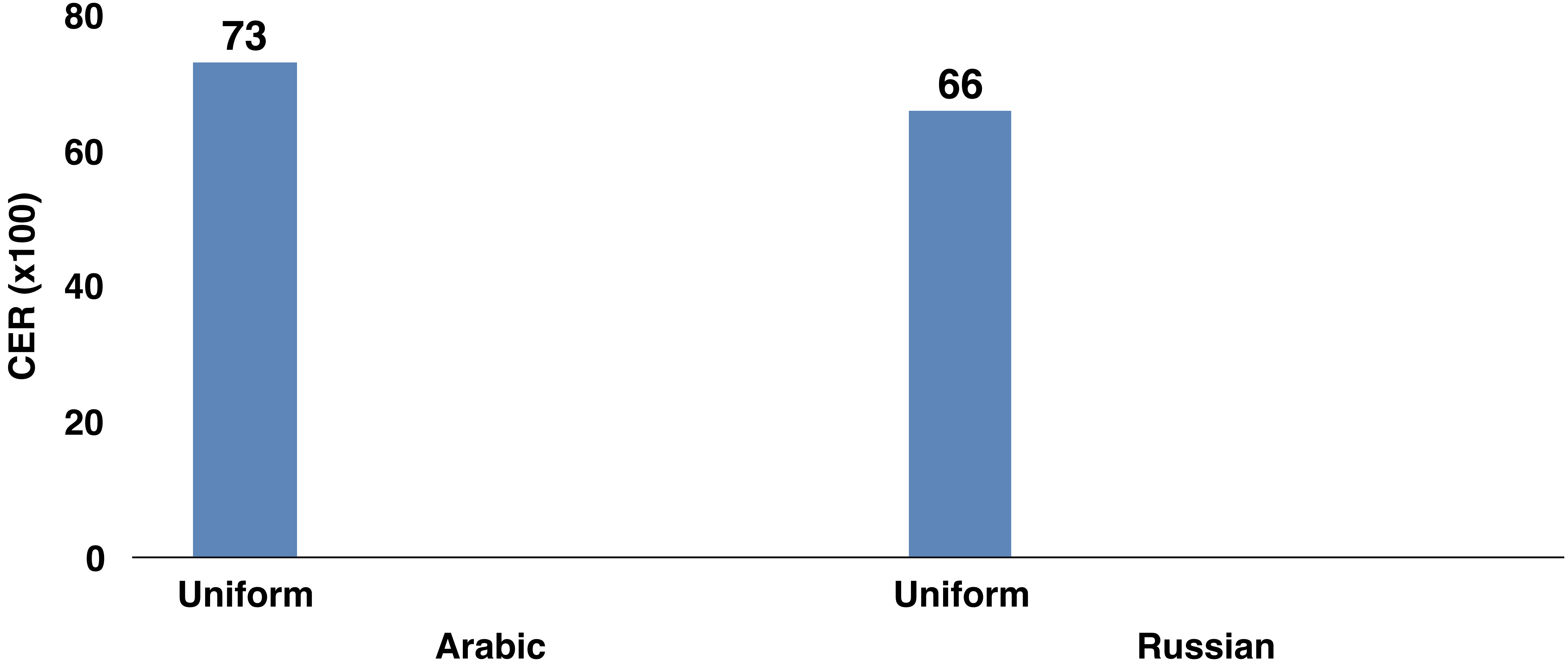
- Unsupervised model without inductive bias has high error rate



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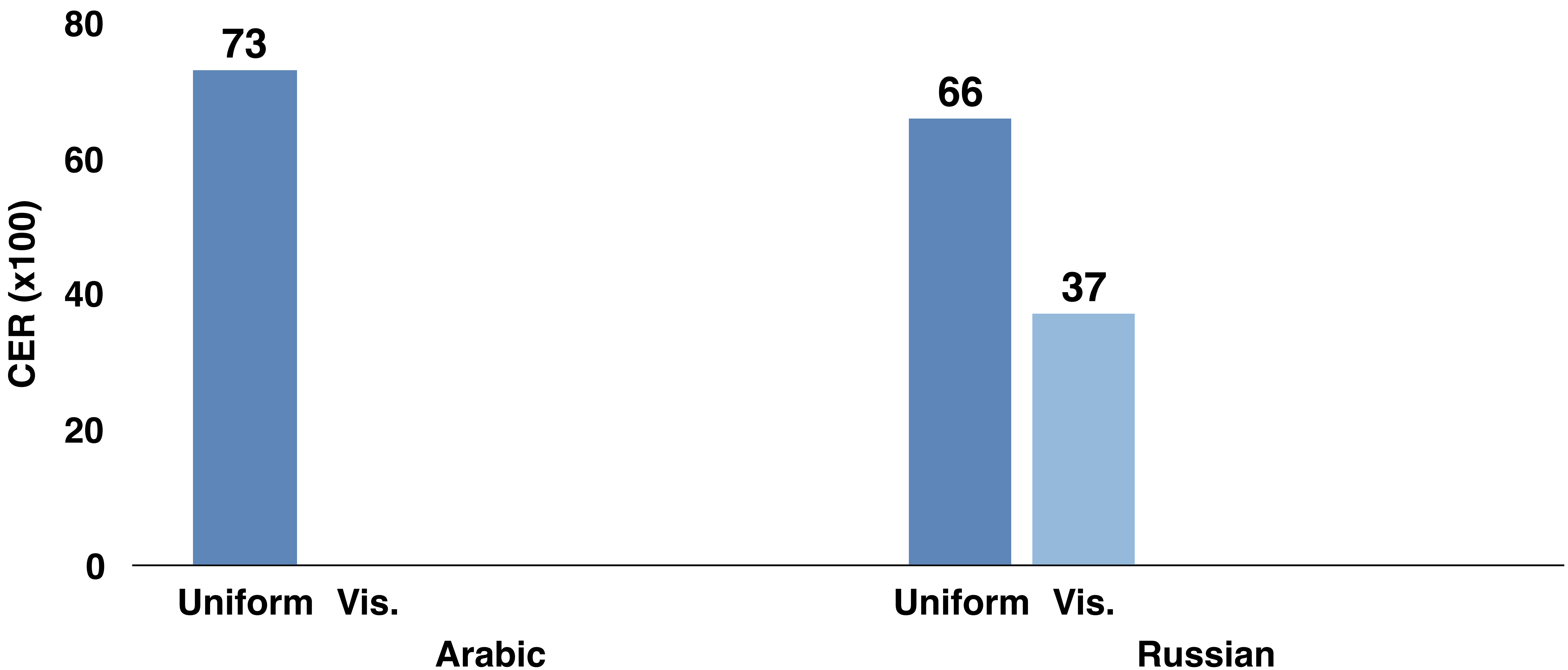

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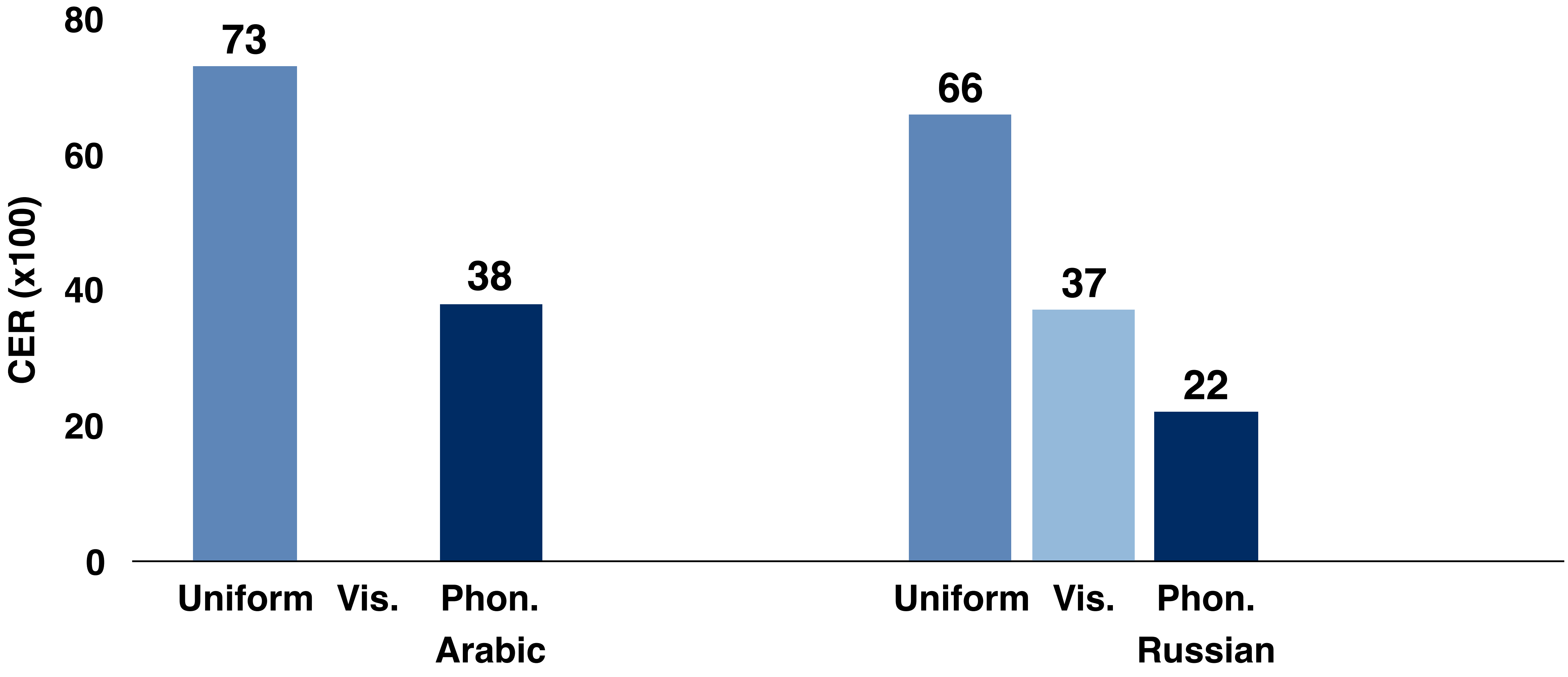

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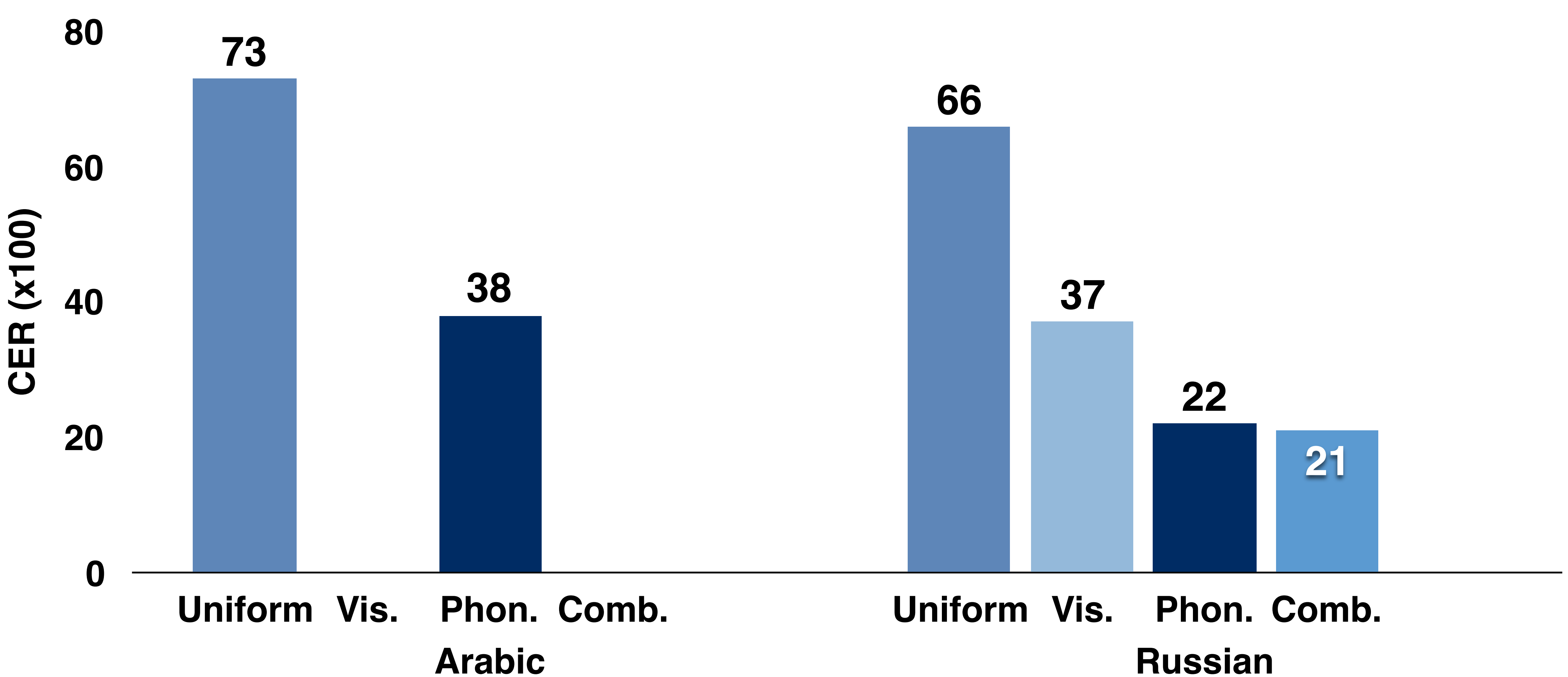

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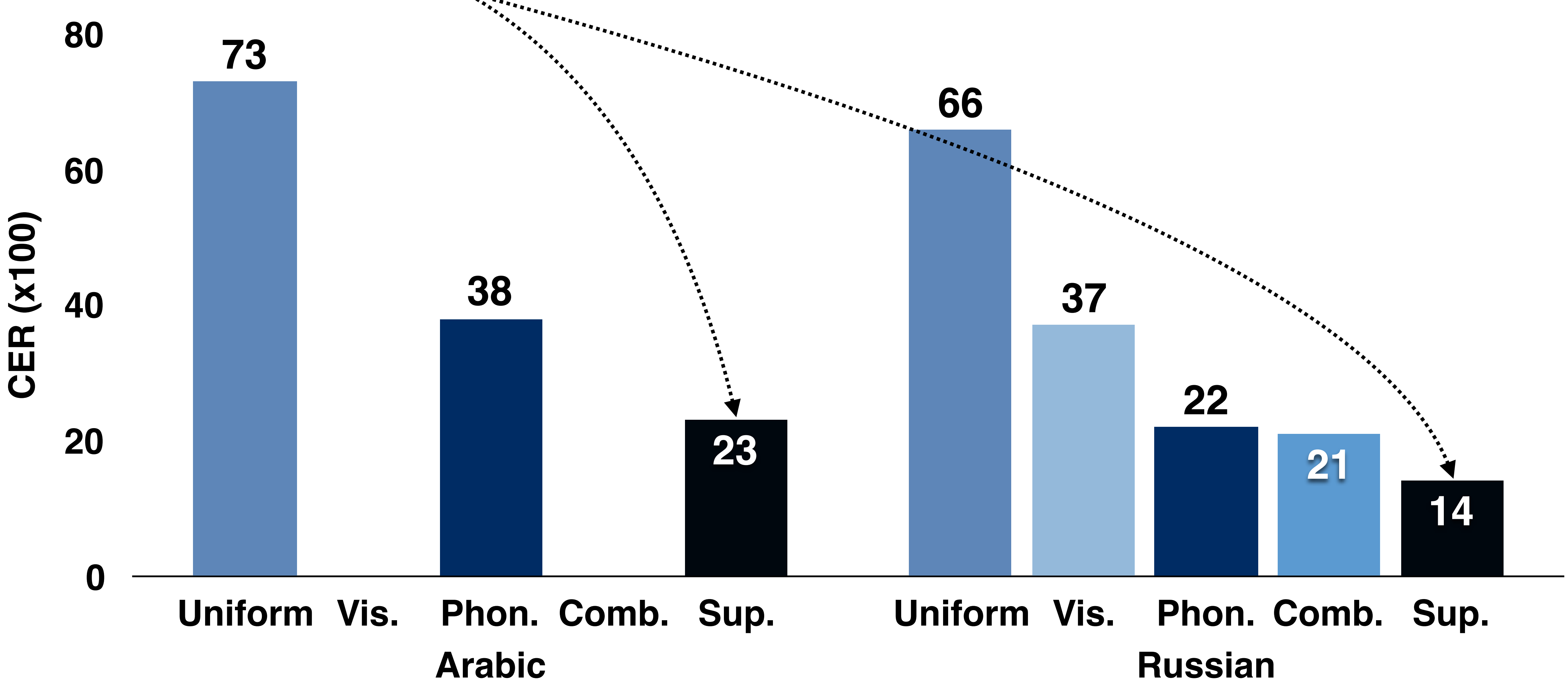
- Supervised skyline compares effect of annotation vs. priors



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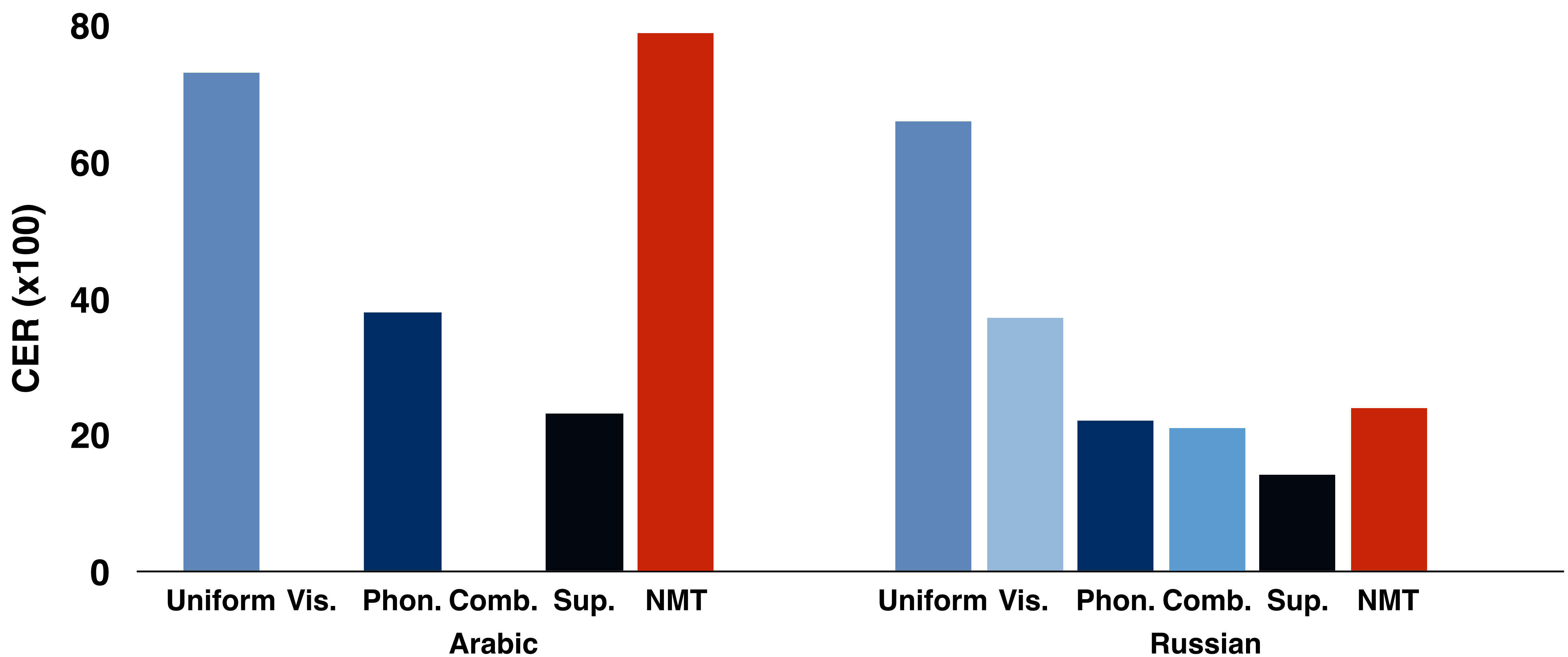

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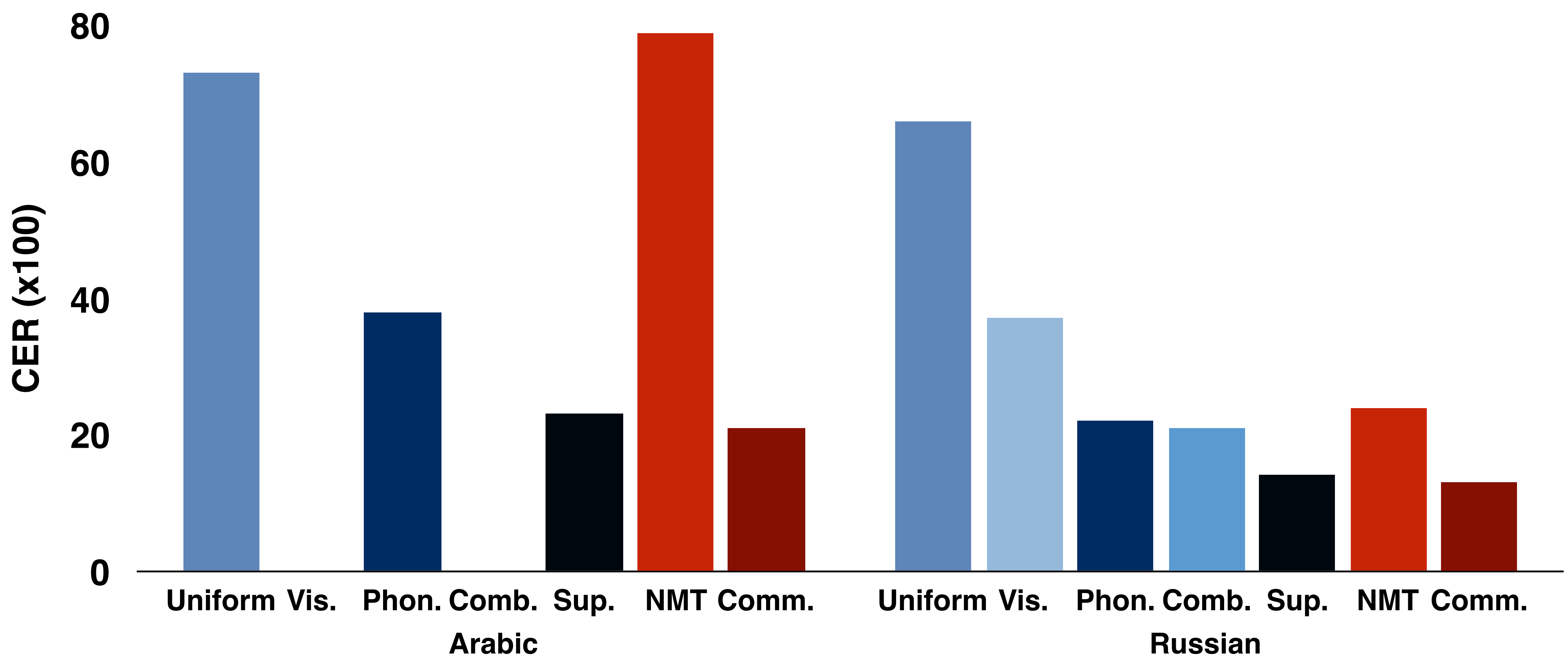
- Unsupervised neural MT (Lample et al.) trained on characters works for Russian
- Nothing beats commercial hand-built systems



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- Future work
  - Explicitly operationalizing character similarity
  - User-specific substitution preferences

Questions?

Q&A sessions:

- July 8, 17:00 UTC+0 (1pm EDT)
- July 8, 21:00 UTC+0 (5pm EDT)

github.com/ryskina/romanization-decipherment

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