Generative Models of Monolingual and Bilingual Gappy Patterns

Kevin Gimpel Noah A. Smith

Overview

- We present models that generate text using patterns with gaps
- Posterior inference allows us to discover the most salient gappy patterns in a corpus

  e.g., *not only* __ *but* *either* __ *or*
- We validate the models by including patterns as features in a phrase-based MT system
- Code is available: `www.ark.cs.cmu.edu/MT`

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Motivation

- Gappy translation units have received a lot of attention recently
  - Mostly bilingual: Simard et al. (2005), Chiang (2005), Galley and Manning (2010), *inter alia*
  - But also monolingual: Xiong et al (2011)
- All rely on heuristics or mutual information
- Can we discover gappy patterns using generative models?

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Monolingual Pattern Models

- "Unigram" model: patterns generated independently
- Main intuition: words in a pattern are generated all at once
- Bayesian nonparametric priors and posterior inference favor the use of a small set of patterns to explain the data

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  - Generate number of word positions
  - Generate number of colors
  - Assign word positions to colors
  - Generate a lexical pattern for each color

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  - Generate number of word positions (n = 16)
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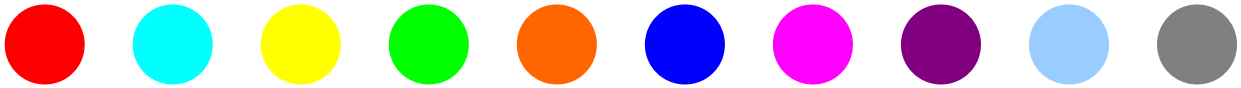

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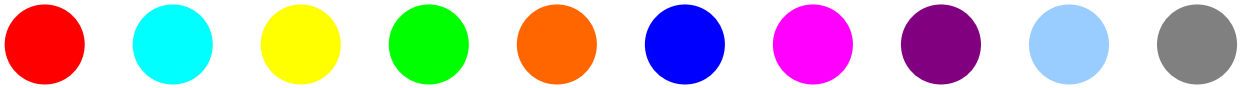

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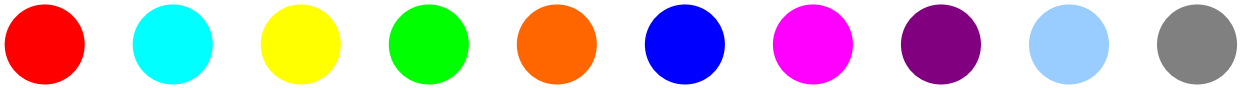

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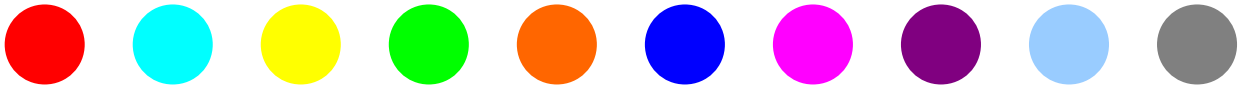

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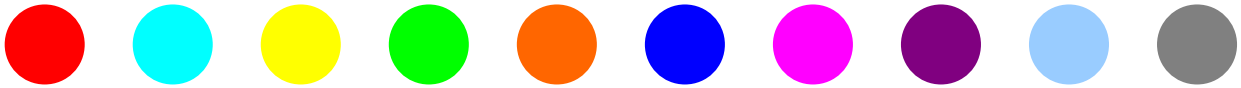

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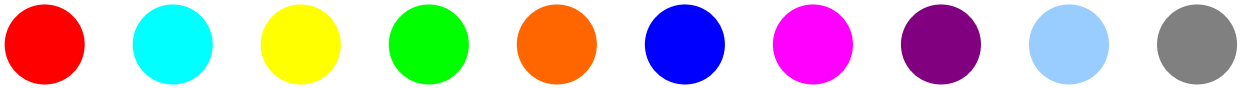


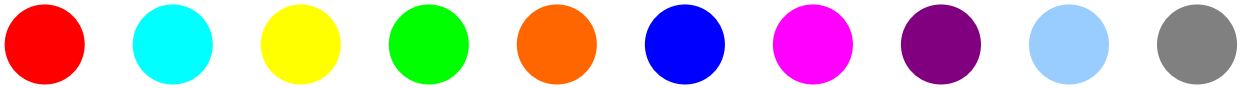
nato must either or

What is a **pattern**?

A sequence of symbols, possibly including the special symbol "__" which is used to indicate a gap of nonzero length

Examples:

nato	the united states
must	according to the __ ,
either __ or	countries __ their __ the united states



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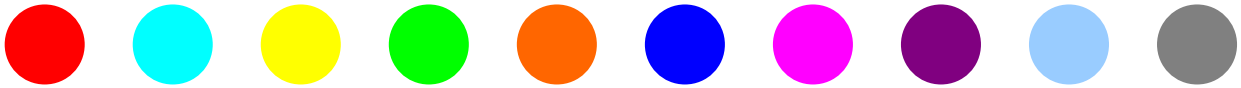

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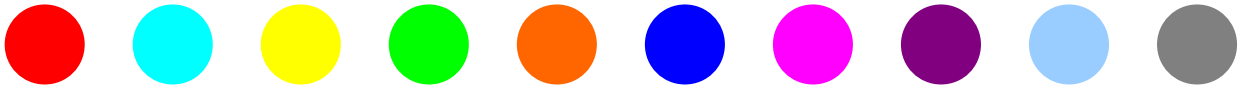

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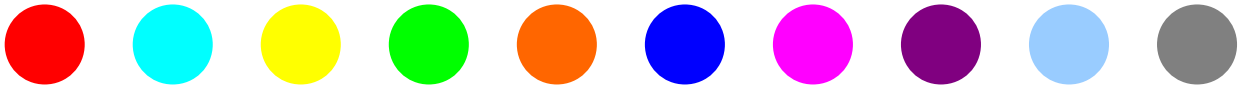

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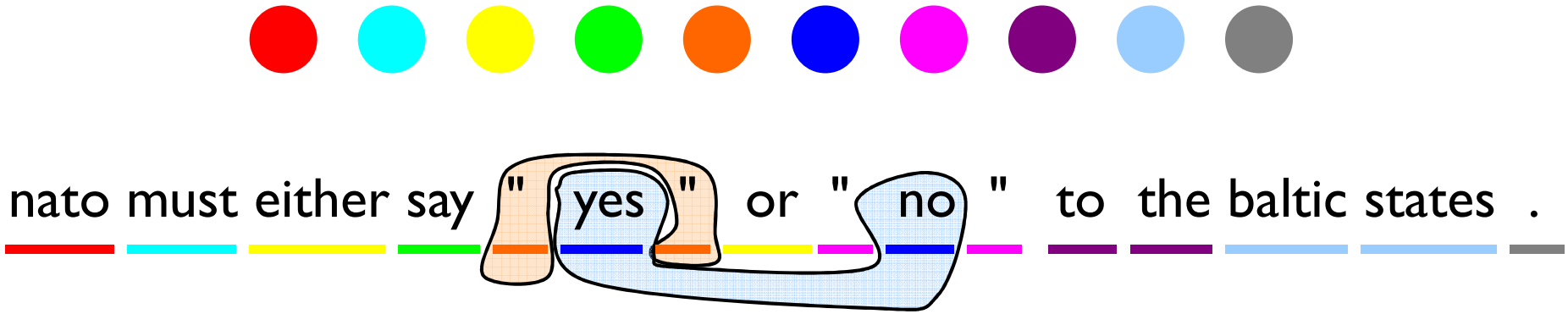

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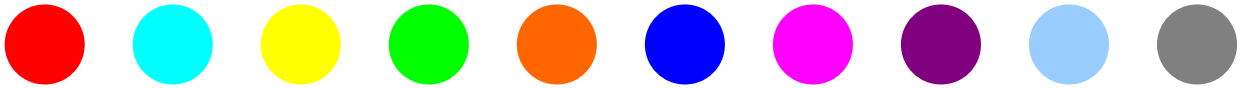

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Nonparametric Priors

- We use a single multinomial distribution over patterns ("unigram pattern model")
- Dirichlet process prior for this multinomial

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Inference

- Goal:
  - Given a corpus, obtain an estimate for how probable each pattern is
- To do this:
  - Obtain samples from posterior distribution over color assignments
  - Compute pattern counts from samples

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- Goal:
  - Given a corpus, obtain an estimate for how probable each pattern is
- To do this:
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  - We use collapsed Gibbs sampling to marginalize out the multinomial distribution over patterns

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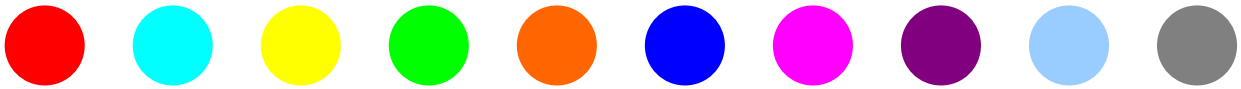
Gibbs Sampling

- Go through each word and sample a new color



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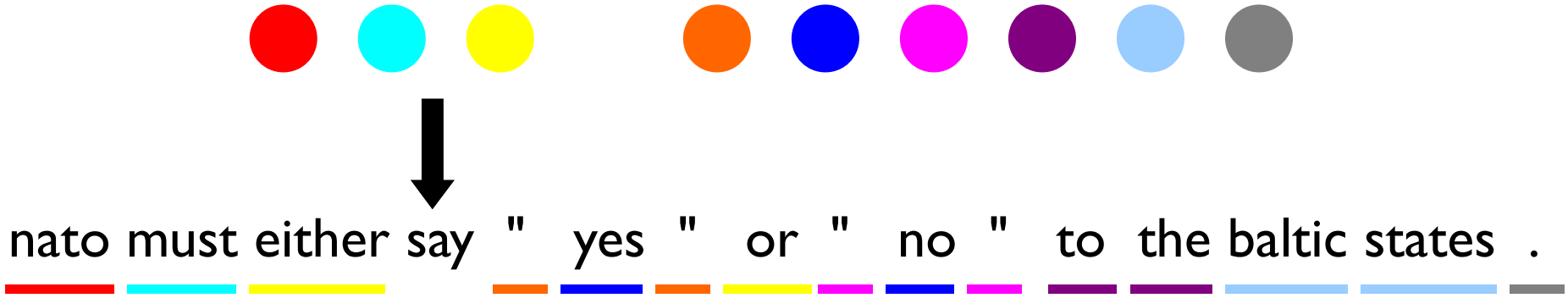

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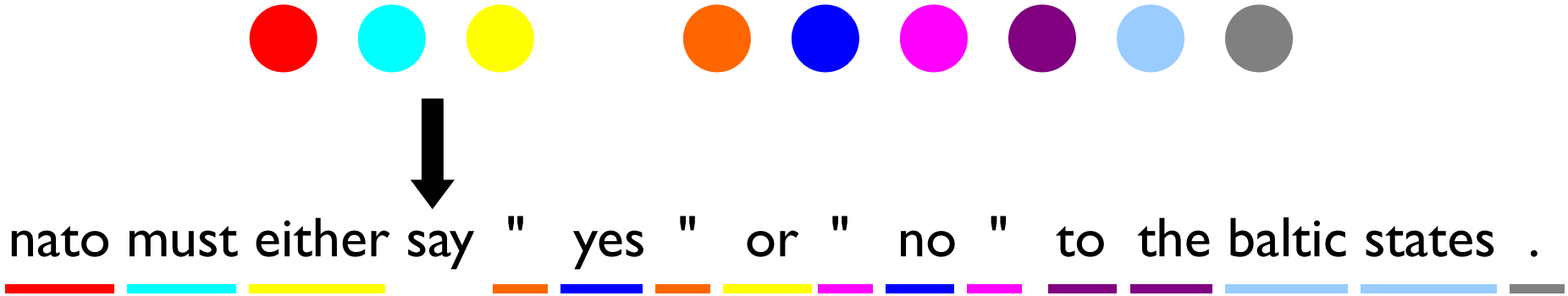

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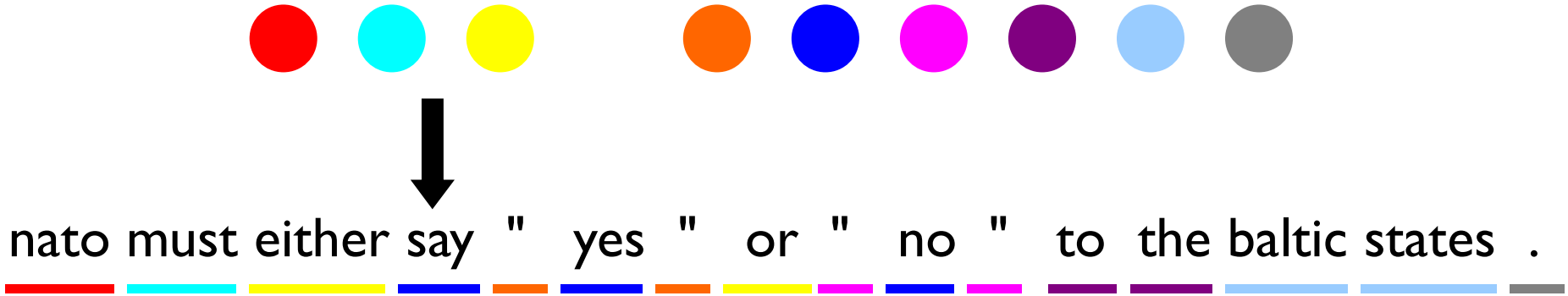

Gibbs Sampling

- We run sampling for 600 iterations on 125,000 sentences of English news commentary text
- After burn-in, we average pattern counts across all samples

Most Probable Patterns

.	the __ " __ "	in __ , __ in	, however ,
" __ "	the united states	america 's	" __ " __ " __ "
-- __ --	rather than	more than	does not
(__)	as __ as	china 's	why __ ?
the __ of	the __ of __ in	the __ of __ ,	country 's
, __ , __ ,	the __ is	prime minister	, __ the __ of
the __ (__)	not only __ but	russia 's	its own
both __ and	the	europe 's	from __ to
have been	it is __ that	is	part of
the __ of __ and	should be	what __ ?	the __ between __ and
more __ than	their own	the world 's	such as __ ,
- __ -	based on	between __ and	these
as well	of __ " __ "	developing countries	either __ or
this	not __ , but	climate change	economic growth
, __ " __ "	has been	the __ of __ 's	european union

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Sorting by Conditional Probability

academy ___ sciences	treasury secretary ___ geithner	at ___ ghraib
beijing ___ shanghai	sooner ___ later	rule ___ law
booms ___ busts	first ___ foremost	free ___ fair
council ___ advisers	played ___ role	neither ___ nor
dominicans ___ haitian	down ___ road	across ___ border
flemish ___ walloons	freedom ___ expression	clash ___ civilizations
gref ___ program	at ___ disposal	estonia ___ lithuania
heat ___ droughts	take ___ granted	within ___ framework
humanitarian ___ displaced	- ___ -	window ___ opportunity
karnofsky ___ hassenfeld	at ___ expense	solve ___ problem
kazakhstan ___ kyrgyzstan	taken ___ granted	paid ___ price
portugal ___ greece	billions ___ dollars	taking ___ account
regulators ___ supervisors	answer ___ yes	during ___ period
sine ___ non	poland ___ slovakia	lender ___ last
stalin ___ mao	ukraine ___ orange	positive ___ negative

Using a Product of Experts

-- ___ --	how ___ ?	we ___ our	his ___ his
(___)	the ___ (___)	over ___ past	some ___ others
- ___ -	on ___ basis	prevent ___ from	may ___ be
both ___ and	less ___ than	in ___ way	as ___ as
not only ___ but	on ___ other hand	one ___ another	oil ___ gas
" ___ "	at ___ level	political ___ economic	at ___ moment
more ___ than	it is ___ that	for ___ reasons	such as ___ and
either ___ or	not ___ , but	at ___ time	question ___ whether
why ___ ?	play ___ role	more ___ more	if ___ then
neither ___ nor	france ___ germany	the rest ___ world	war ___ iraq
what ___ ?	he ___ his	more ___ less	; ___ ;
rule ___ law	allow ___ to	in ___ region	have ___ been
whether ___ or	for ___ first time	rich ___ poor	in ___ cases
around ___ world	china ___ india	as ___ whole	war ___ terror
has ___ been	what ___ do	on ___ scale	at ___ cost

Punctuation

-- ___ --	how ___ ?	we ___ our	his ___ his
(___)	the ___ (___)	over ___ past	some ___ others
- ___ -	on ___ basis	prevent ___ from	may ___ be
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Connectives and Constructions

-- ___ --	how ___ ?	we ___ our	his ___ his
(___)	the ___ (___)	over ___ past	some ___ others
- ___ -	on ___ basis	prevent ___ from	may ___ be
both ___ and	less ___ than	in ___ way	as ___ as
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Agreement

-- ___ --	how ___ ?	we ___ our	his ___ his
(___)	the ___ (___)	over ___ past	some ___ others
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Topicality

-- ___ --	how ___ ?	we ___ our	his ___ his
(___)	the ___ (___)	over ___ past	some ___ others
- ___ -	on ___ basis	prevent ___ from	may ___ be
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Prepositional Phrases

-- ___ --	how ___ ?	we ___ our	his ___ his
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- How does this differ from word trigger pairs derived from mutual information (Rosenfeld, 1994)?
- The X __ Y pairs we extract are similar to his pairs
- We also model collocations and larger patterns:
  - X Y Z
  - X Y __ Z
  - X __ Y __ Z
  - X Y __ Z __ W __ V
  - etc.
- Generative models are also amenable to extensions…

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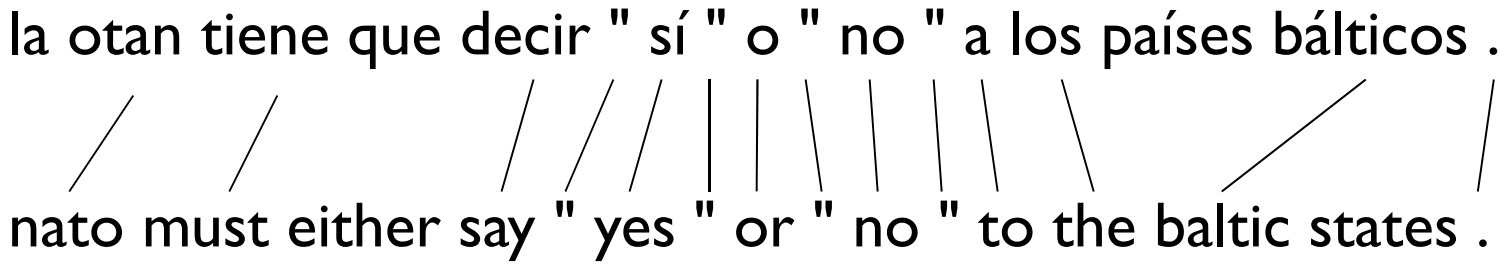
Modeling Bilingual Patterns



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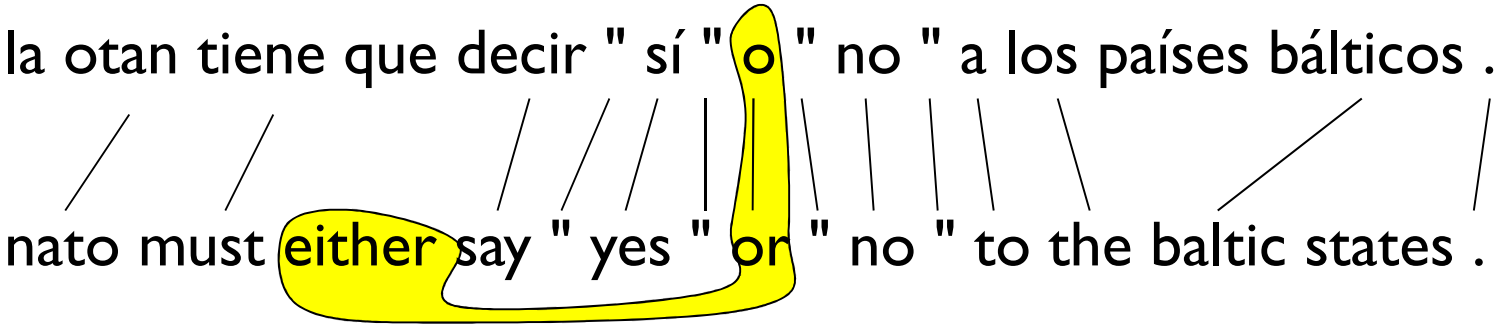

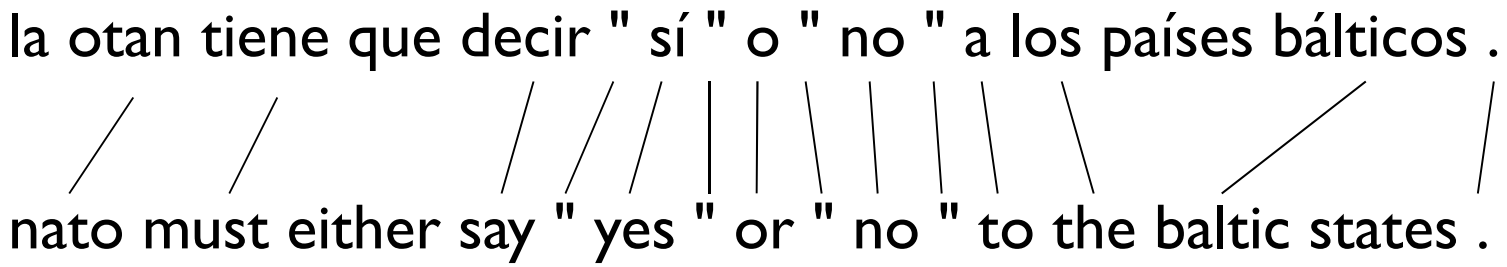

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  - Generate n target word positions, n′ source positions
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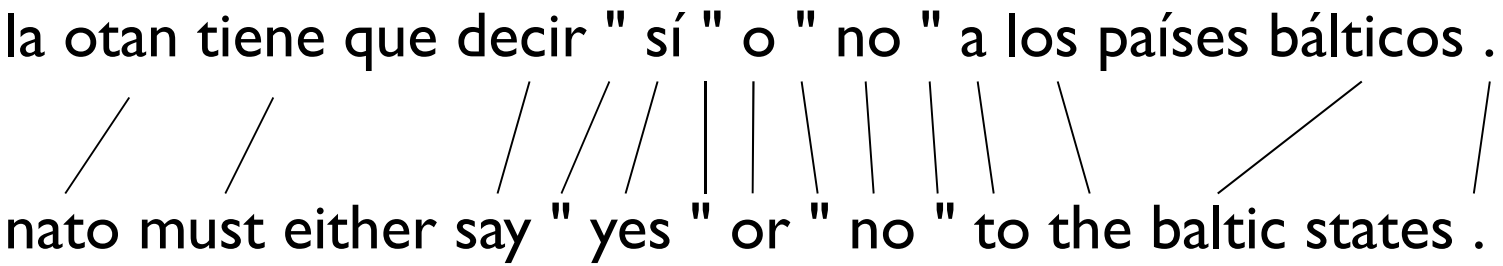

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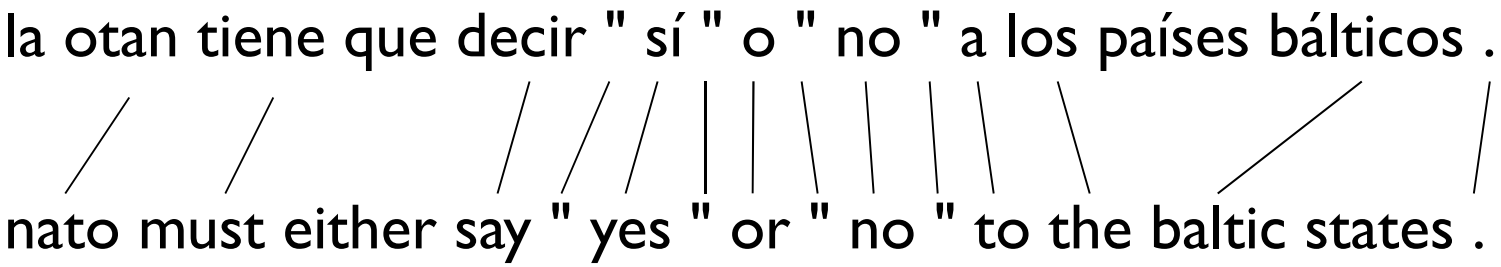

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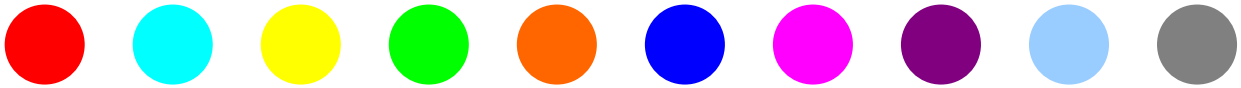

la otan tiene que decir " sí " o " no " a los países bálticos .

nato must either say " yes " or " no " to the baltic states .

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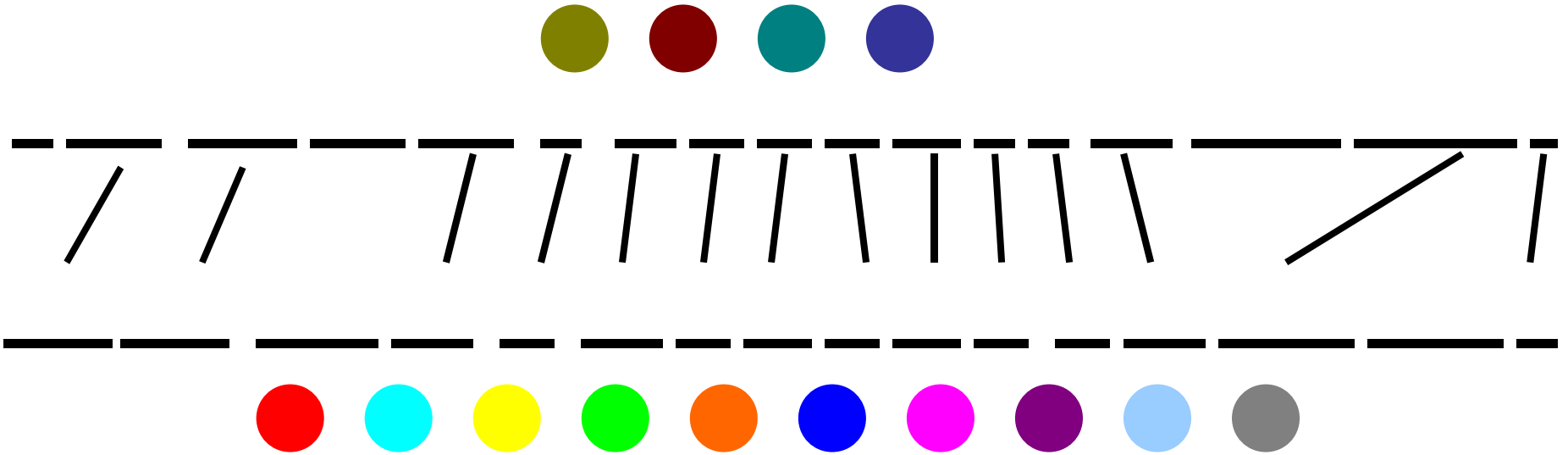

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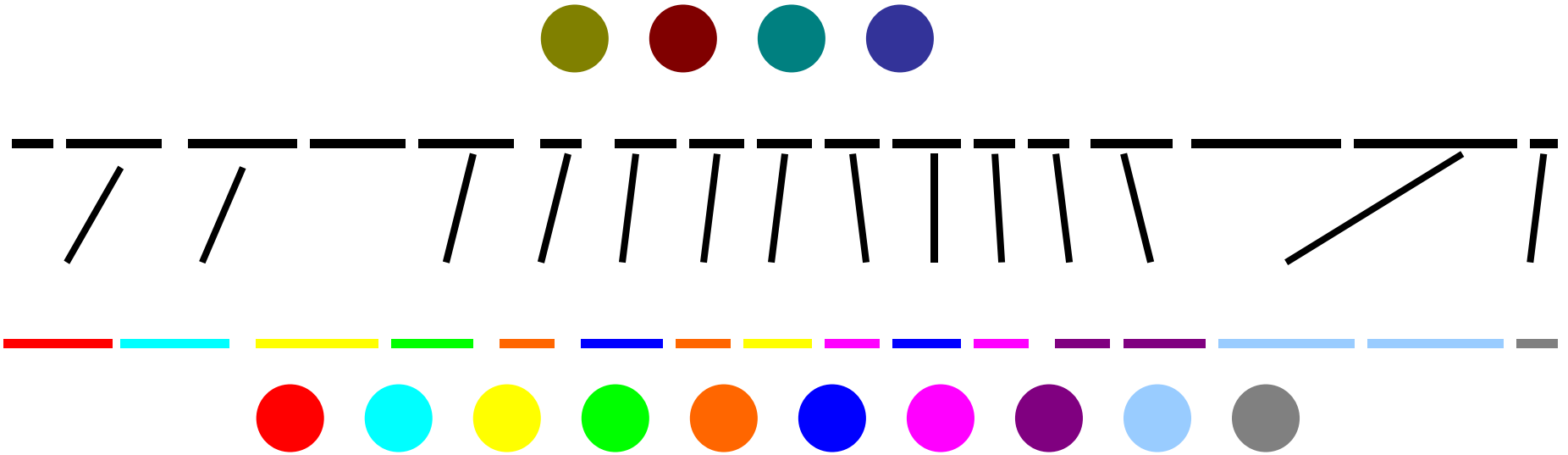

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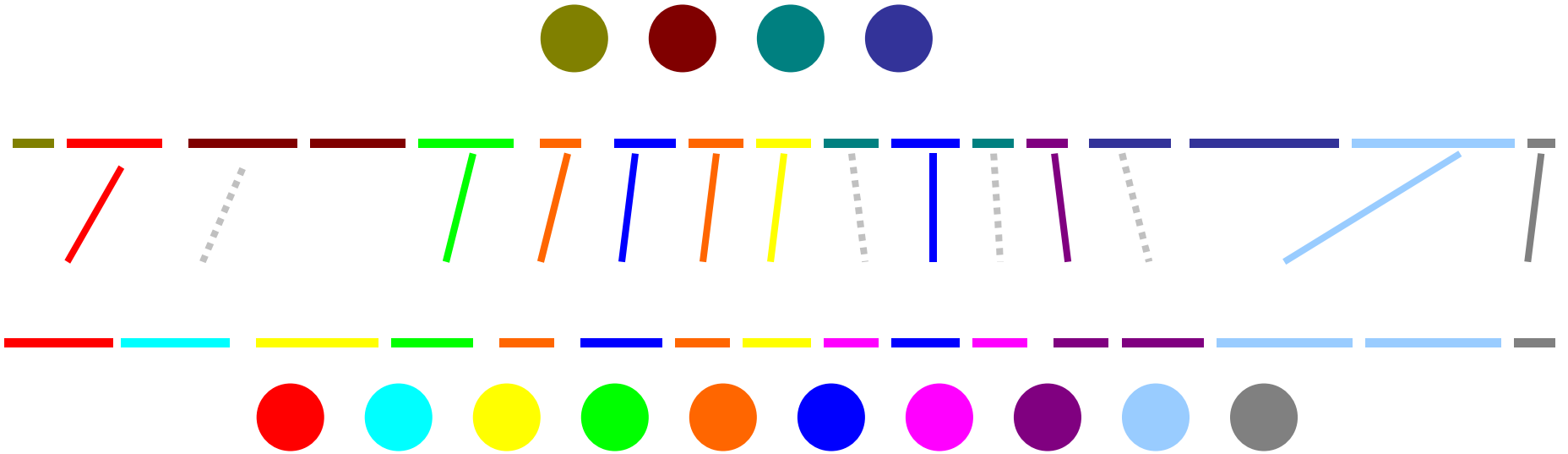

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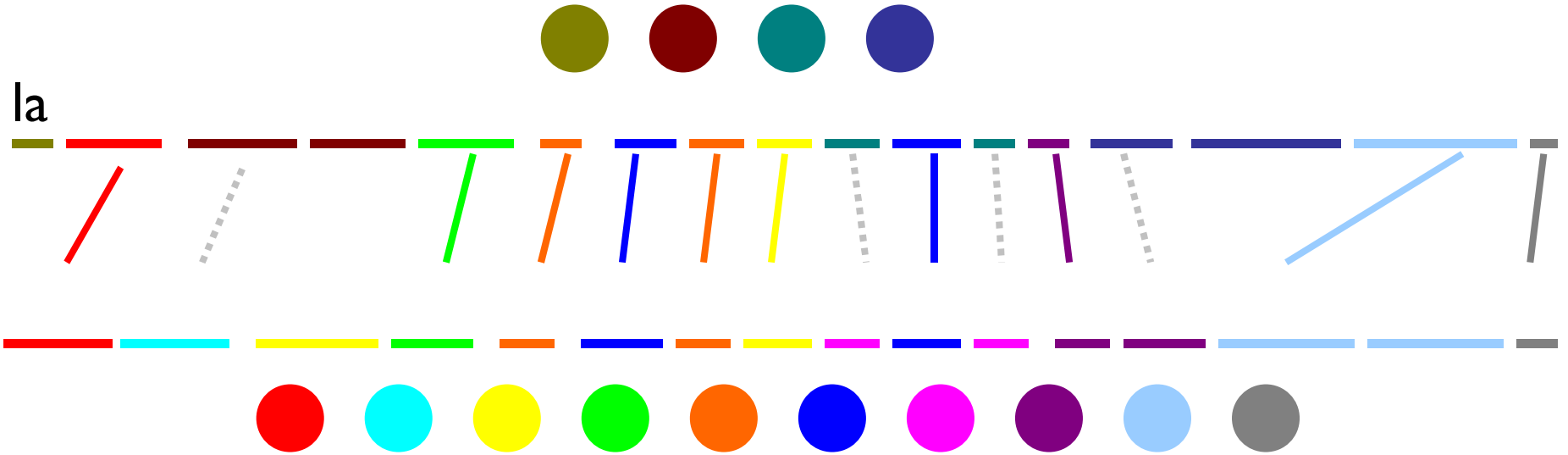

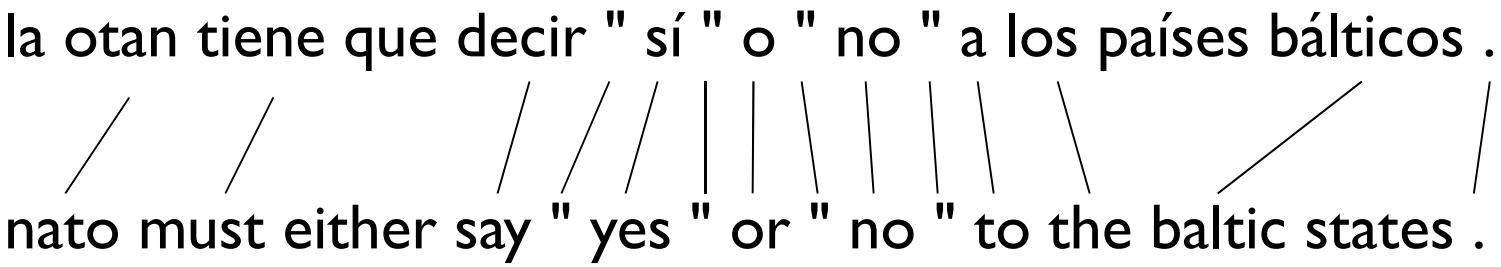

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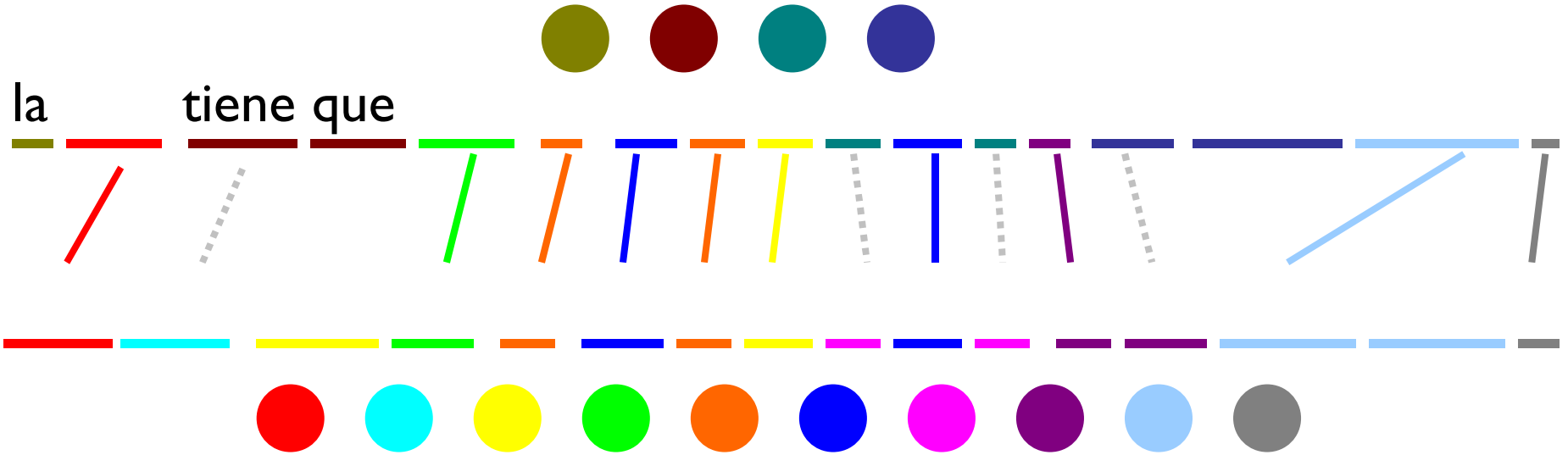

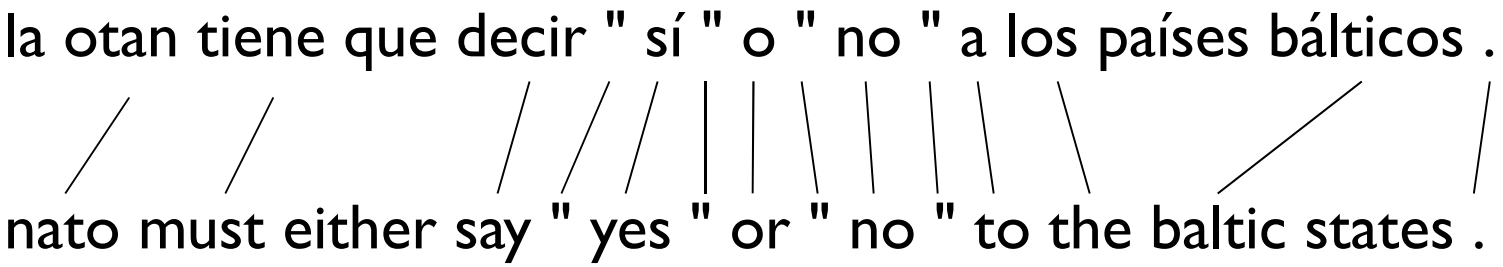

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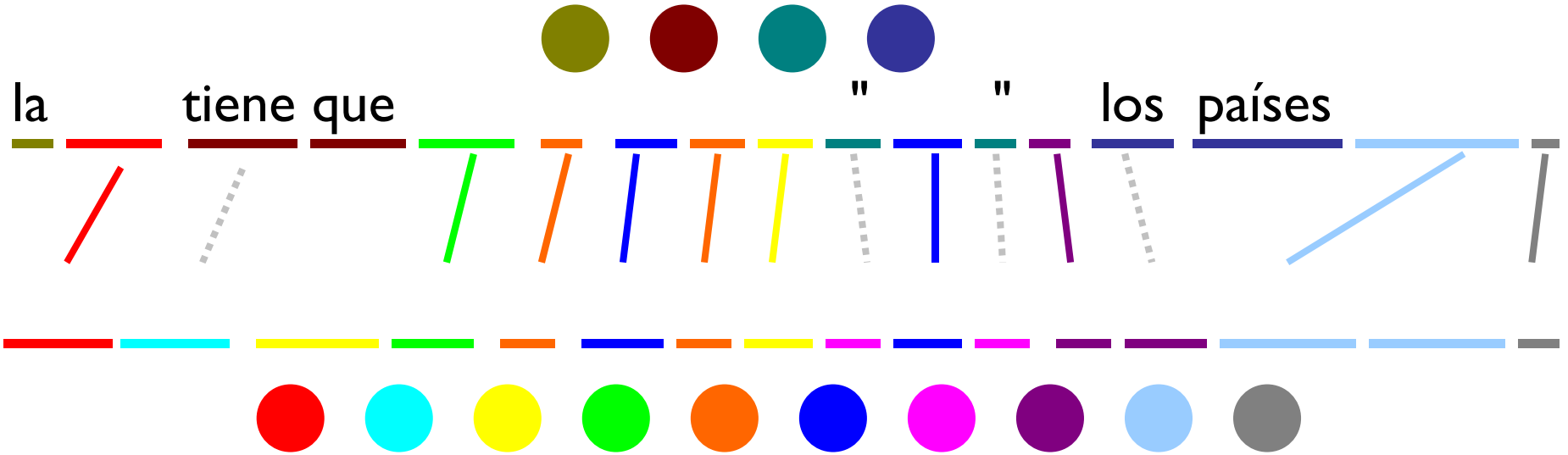

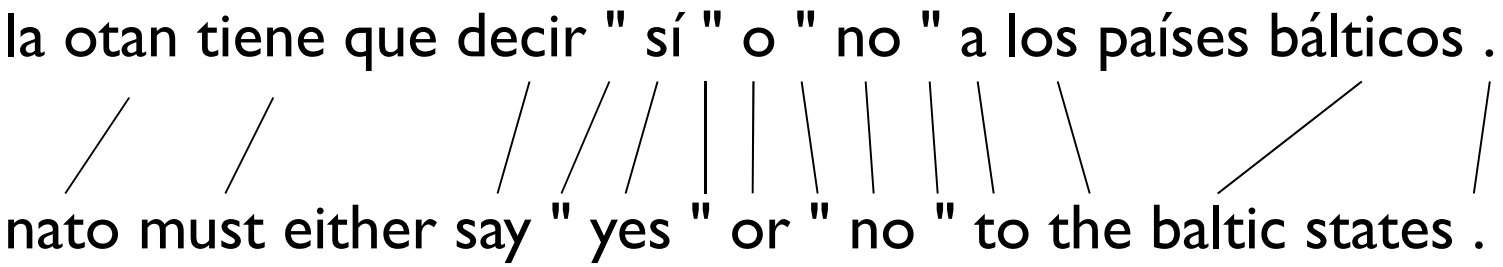

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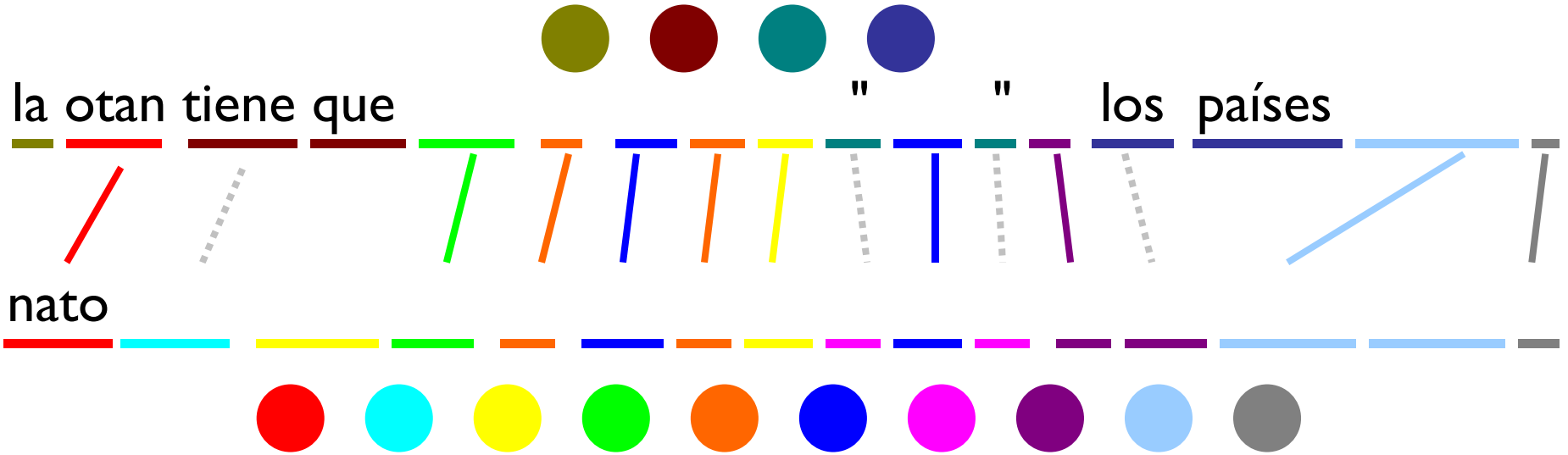

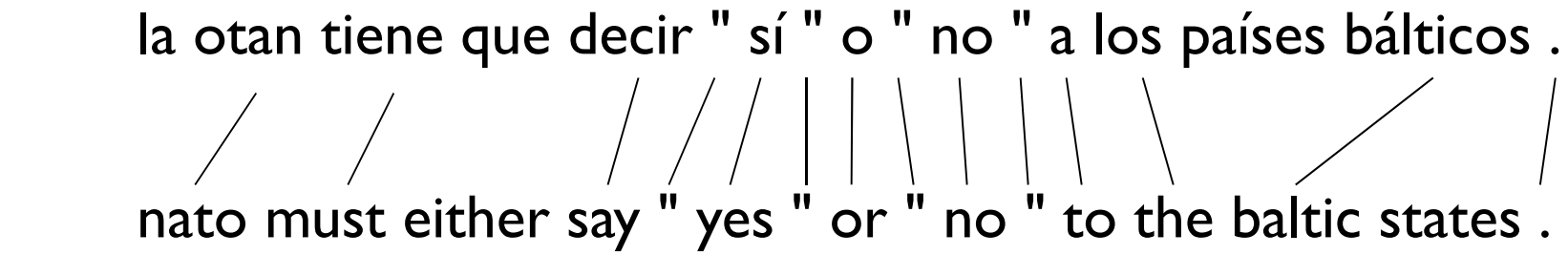

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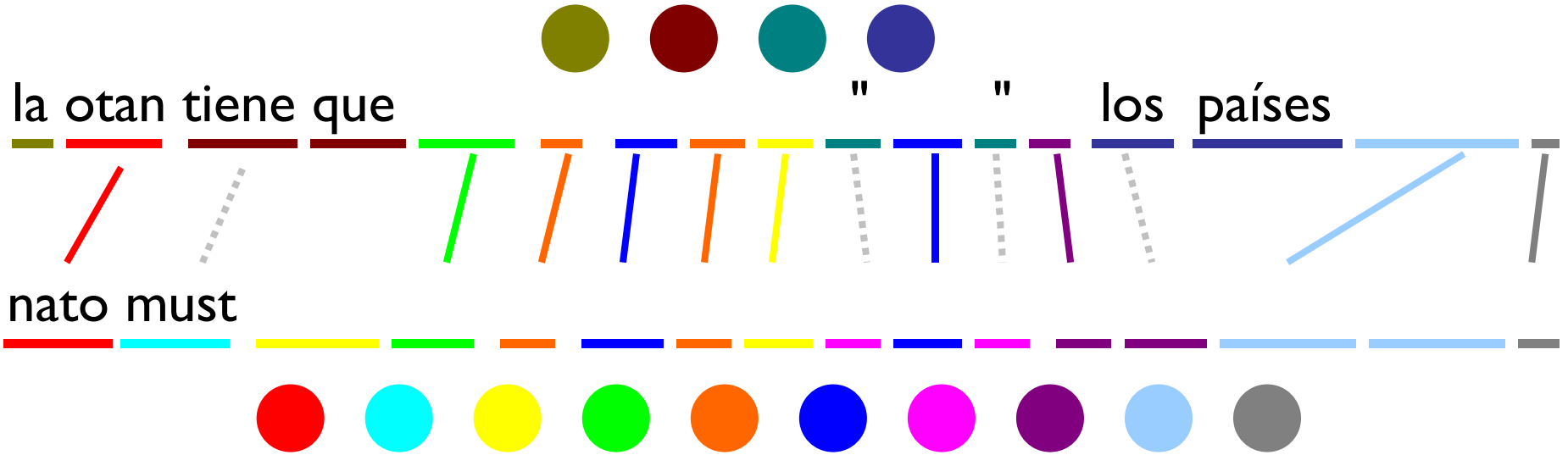

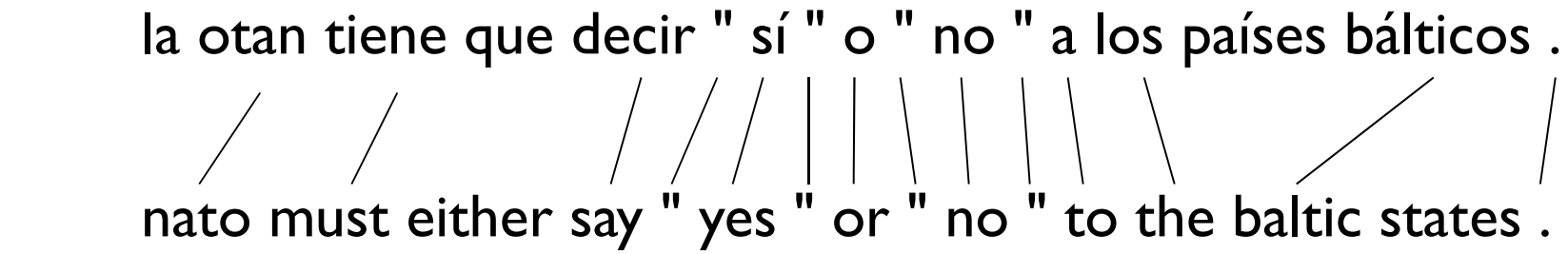

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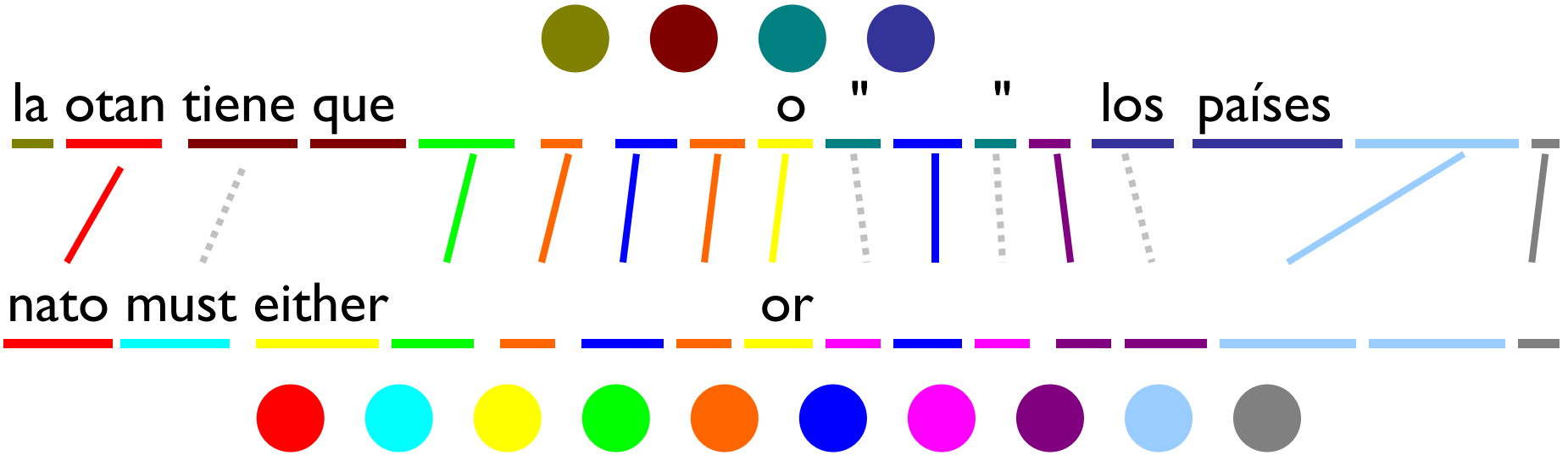

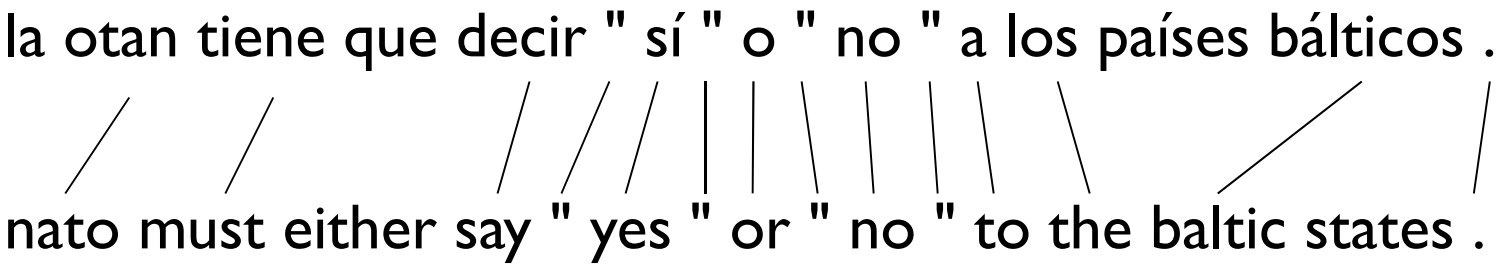

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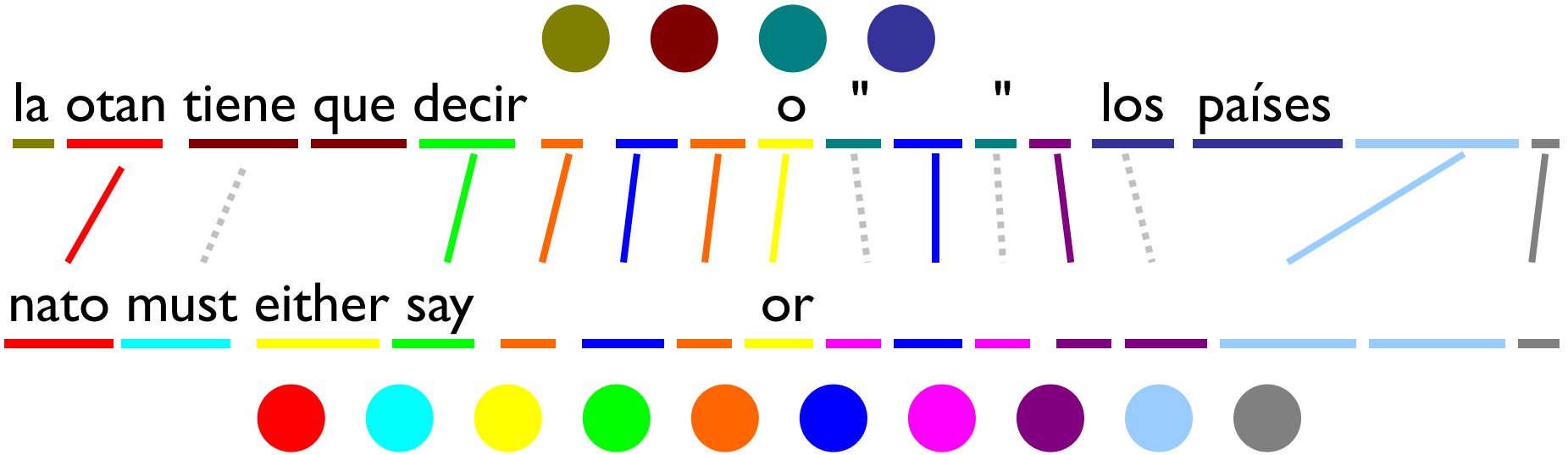

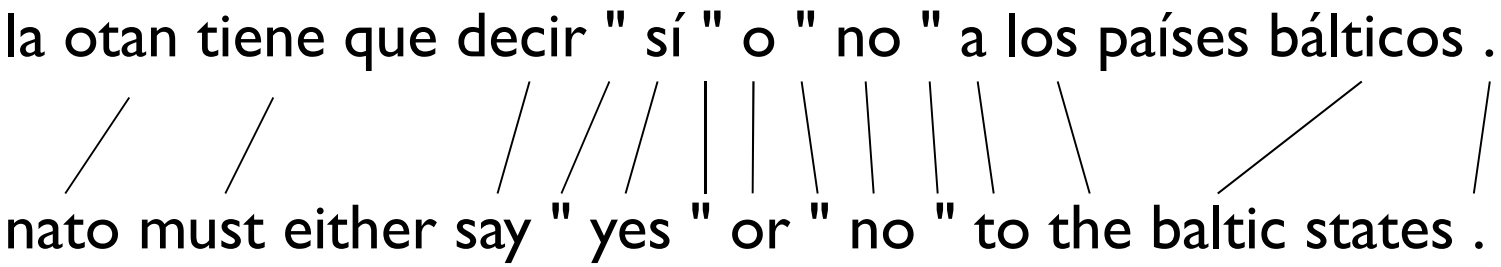

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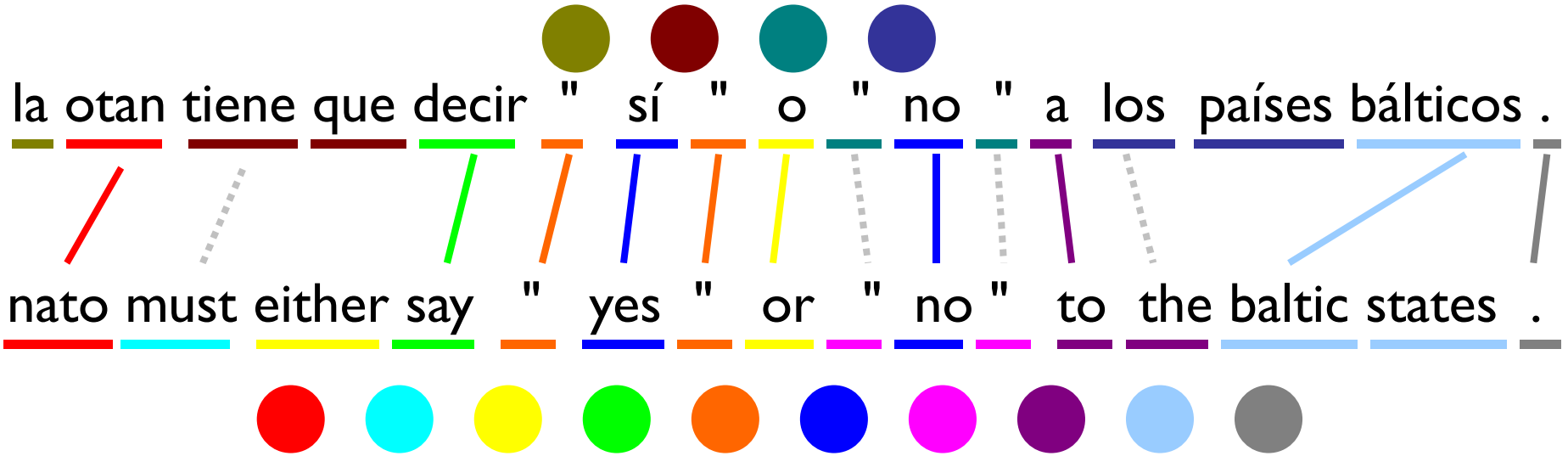

Inference with Bilingual Pattern Models

- Gibbs sampler similar to monolingual model, with a few extra moves (see paper and code)
- Inference run for 300 iterations
- Examples:

we must(debemos)	they ___ their(sus)
we are(estamos)	their(sus) ___ their(sus)
we can(podemos)	he ___ his(sus)
either ___ or(o)	it ___ its(sus)

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Experiments

- We added count features for individual patterns
- Monolingual patterns:
  - 10k lexical patterns
  - 15k patterns on Brown clusters
- Bilingual patterns:
  - 5k word/word, 5k word/cluster, 5k cluster/cluster
- Features are **non-local** since they can match anywhere in the derivation
- Features incorporated via cube pruning of phrase lattices
- Trained using a MIRA-like procedure (simplified from that of Chiang et al., 2009)

Experiments

- Chinese-English
  - 300k sentence pairs from FBIS corpus
  - Tuned on MT03, tested on MT05
  - Trigram LM estimated from English side of parallel corpus + 200M words of Gigaword data
- Spanish-English
  - No improvement; experiments reported in paper

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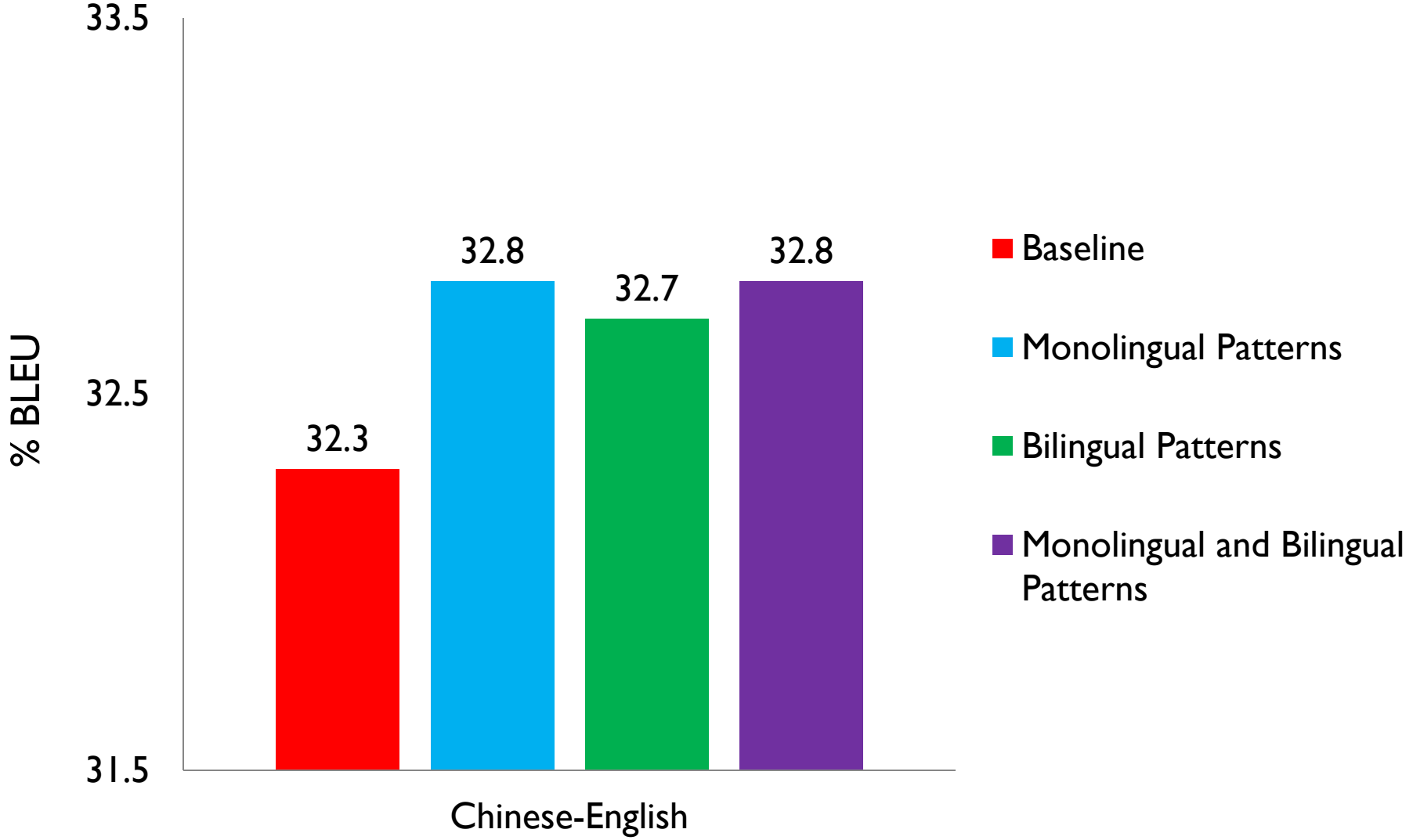
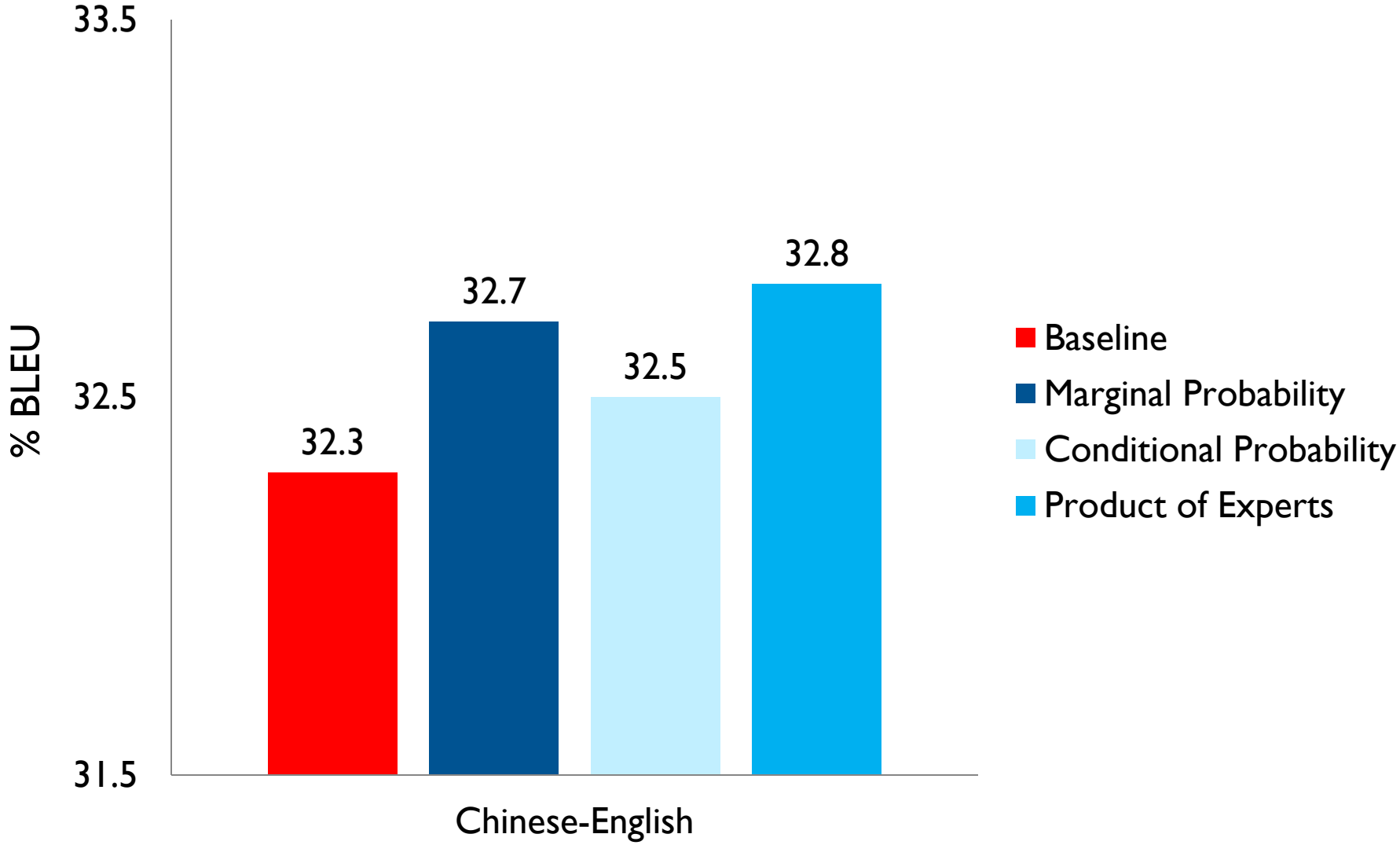
Adding Pattern Features



Comparing Ways of Ranking Patterns



Most Highly-Weighted Features

said that ___ the	of ___ million
however , ___ the	, ___ likely
agence france ___ presse	said that ___ and
's ___ , ___ 's	added ___ "
us ___ iraq	- ___ -
reported ___ the	rate ___ percent

the ___ {media, school, university, election, bank} ___ {made, established, given, taken, reached}
{said, stressed, stated, indicated, noted} that ___ in
{meeting, report, conference, reports, summit} ___ {1, july, june, march, april}
{news, press, spokesman, reporter, consultative} {meeting, ...} ___ {1, july, june, march, april}
{news, press, spokesman, reporter, consultative} ___ {1, july, june, march, april}
the ___ {enterprises, companies, students, customers, others} ___ {enterprises, companies, ...}
{japan, russia, europe, 2003, 2004} ___ {us, japanese, russian, u.s., british}

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Conclusions

- We presented models for discovering gappy patterns in monolingual and parallel text
- Validation of patterns qualitatively and quantitatively in a phrase-based MT system
- Code implementing inference for our models is available: `www.ark.cs.cmu.edu/MT`

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Thanks!

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