

DEPARTMENT OF COMPUTER SCIENCE

Beyond noise: Mitigating the Impact of Fine-grained Semantic Divergences on Neural Machine Translation

Eleftheria Briakou & Marine Carpuat

Supervised Machine Translation (MT)

Typically trained on parallel texts: Sentences considered as translations of each other

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votre père est français

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Typically trained on parallel texts: Sentences considered as translations of each other

votre père est français

your father is french

Parallel texts are not always exact translations



Parallel texts contain fine-grained semantic divergences

Mostly equivalent parallel texts that contain a small number of divergent tokens

votre père est françaisyour father is frenchvotre père est françaisyour parent is french

Parallel texts are not always exact translations



Parallel texts contain coarse-grained semantic divergences

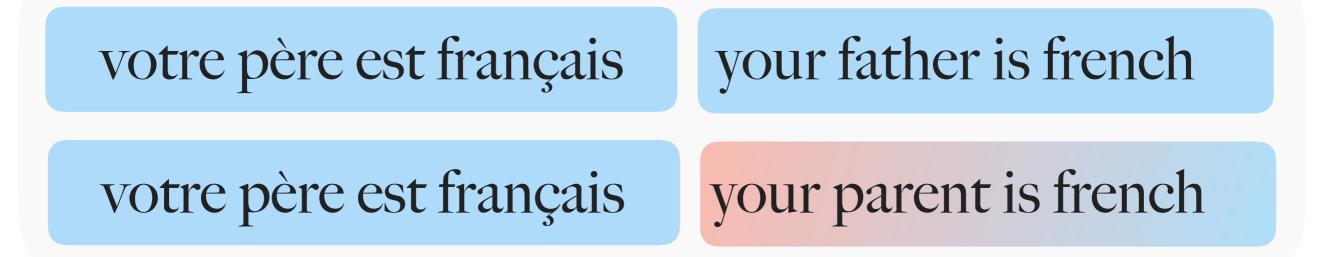
unrelated sentence pairs – noisy training signal

votre père est français	your father is french
votre père est français	your parent is french
votre père est français	who is your father

Coarse-grained semantic divergences are typically excluded from training



Fine-grained semantic divergences are treated as equivalent at MT training



How do fine-grained divergences impact NMT?

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hurt translation quality

more repetitive loops increase prediction uncertainty

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How can we mitigate their negative impact?

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How can we mitigate their negative impact?

by encoding divergences as token factors

 $J(\theta) = \sum \log p(y_t^{(n)} | y_{< t}^{(n)}, x^{(n)}; \theta)$ n = 1 t = 1

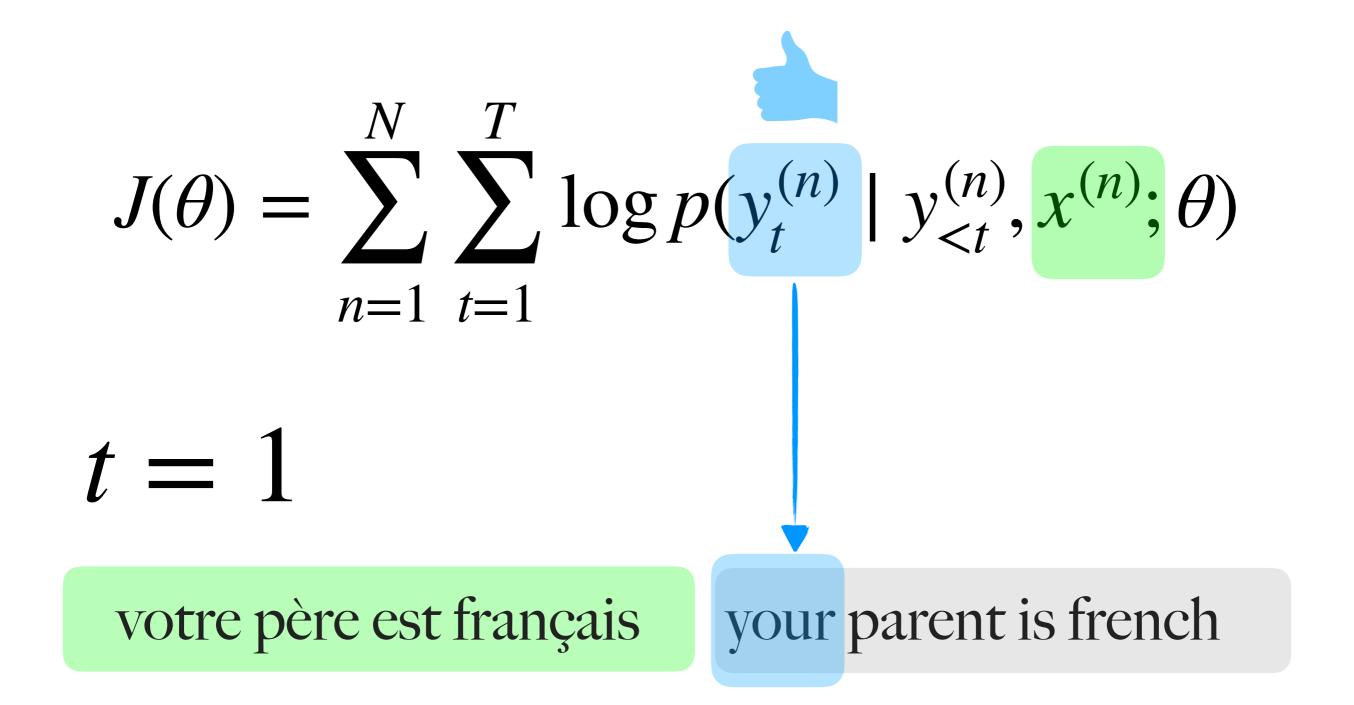
votre père est français

your parent is french

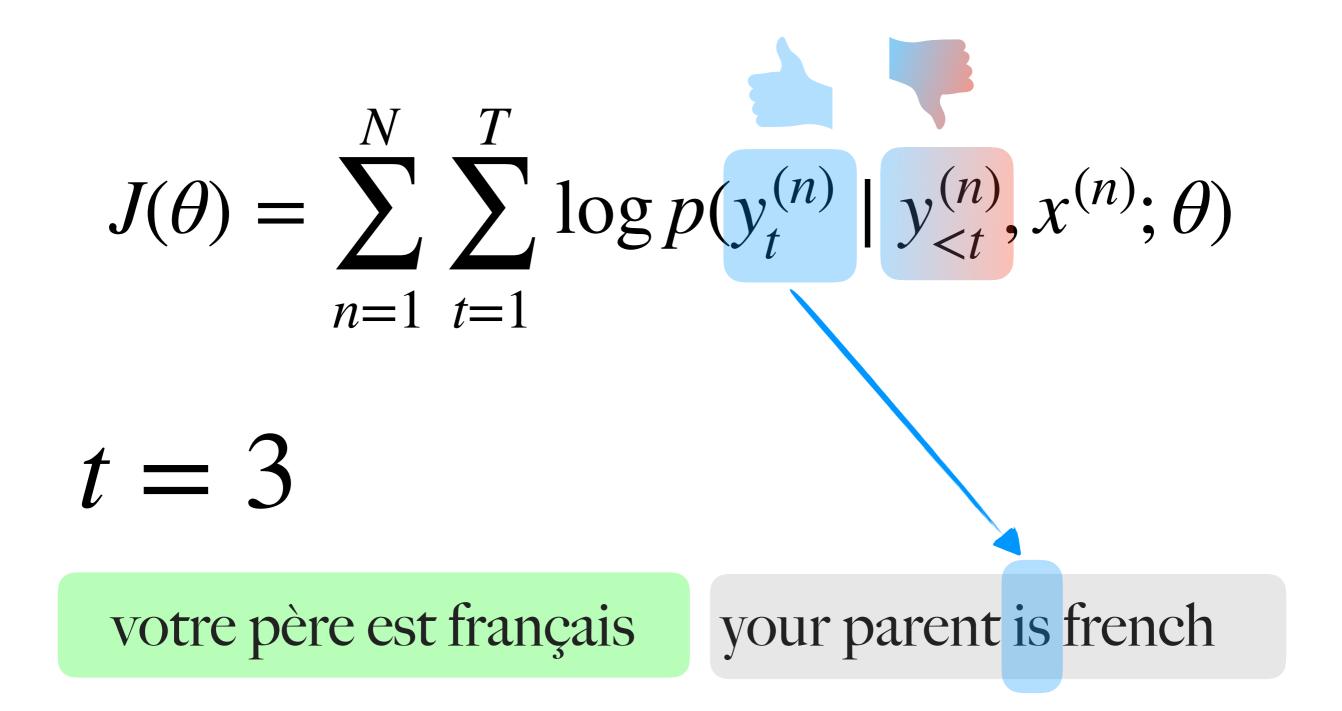
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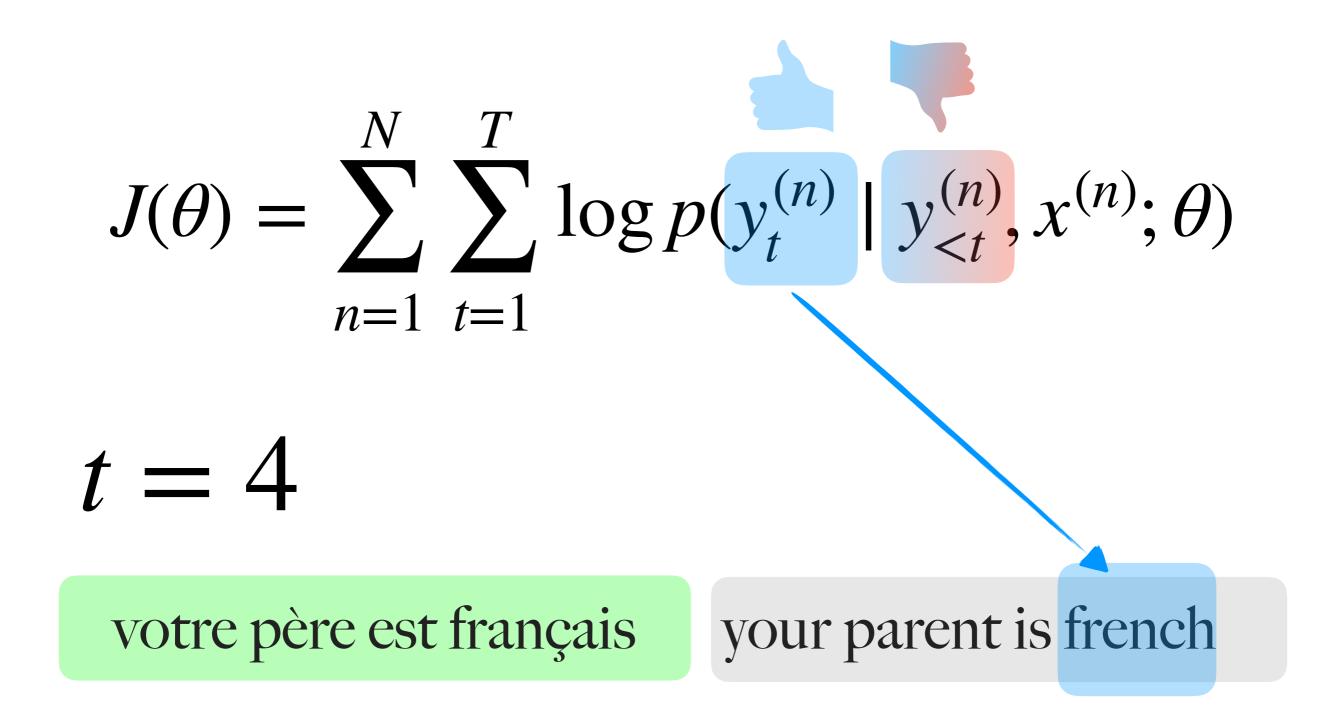
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 $J(\theta) = \sum \log p(y_t^{(n)} | y_{< t}^{(n)}, x^{(n)}; \theta)$ n = 1 t = 1t = 2votre père est français your parent is french





Controlled analysis on artificial divergences

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Controlled analysis on artificial divergences

Experimental Setting

- Training bitext
- Test set
- Language-pair
- NMT architecture : Transformer

- : WikiMatrix (mined)
 - TED
 - French -> English Transformer

Controlled analysis on artificial divergences

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Measuring the impact of synthetic divergences on NMT

EQUIVALENT

ils vous demandent votre aide

they are asking your help

Measuring the impact of synthetic divergences on NMT

EQUIVALENT

ils vous demandent votre aide they are asking your help

PHRASE DELETION

ils vous demandent votre aide

they are asking

Measuring the impact of synthetic divergences on NMT

EQUIVALENT

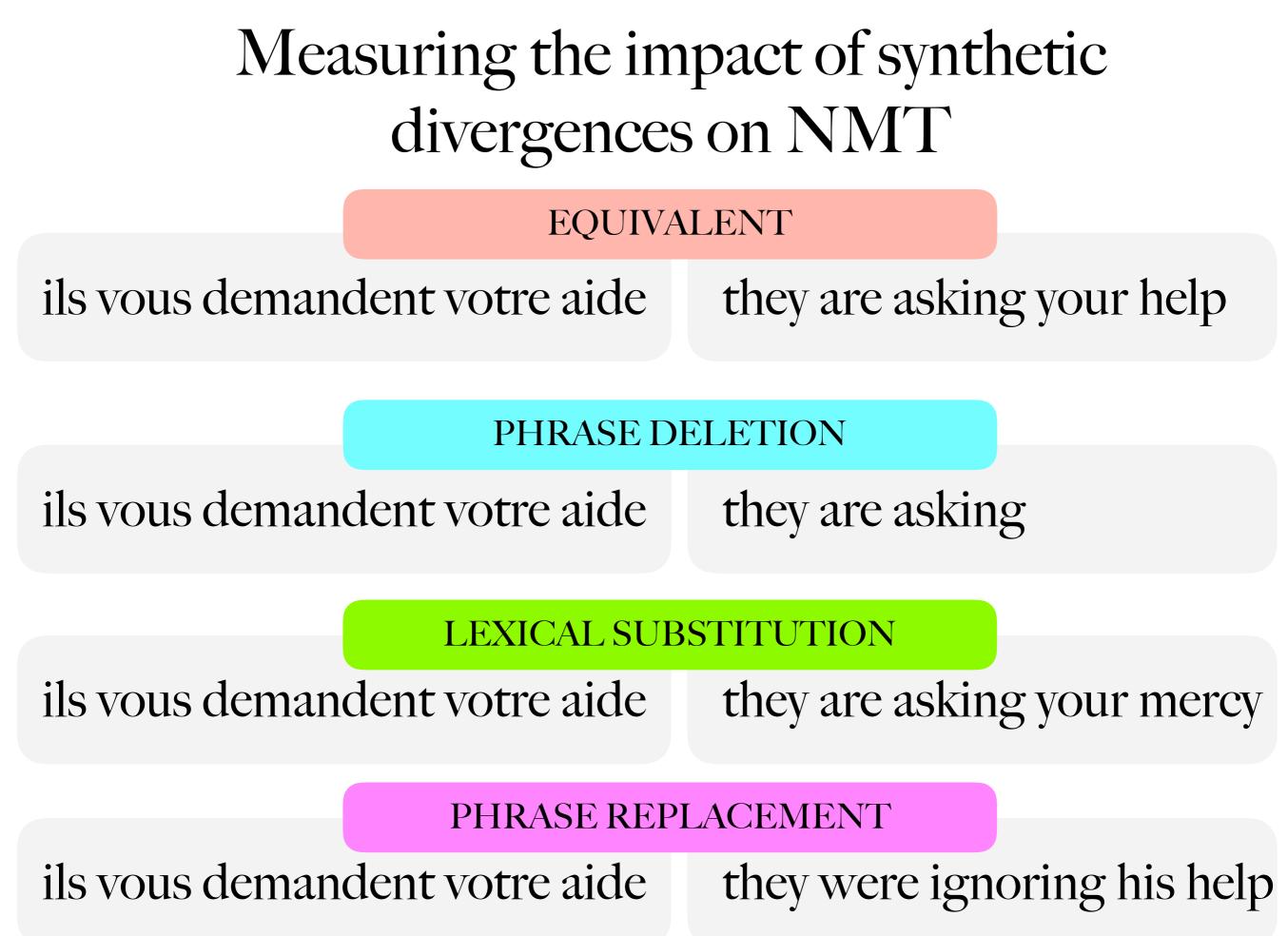
ils vous demandent votre aide they are asking your help

PHRASE DELETION

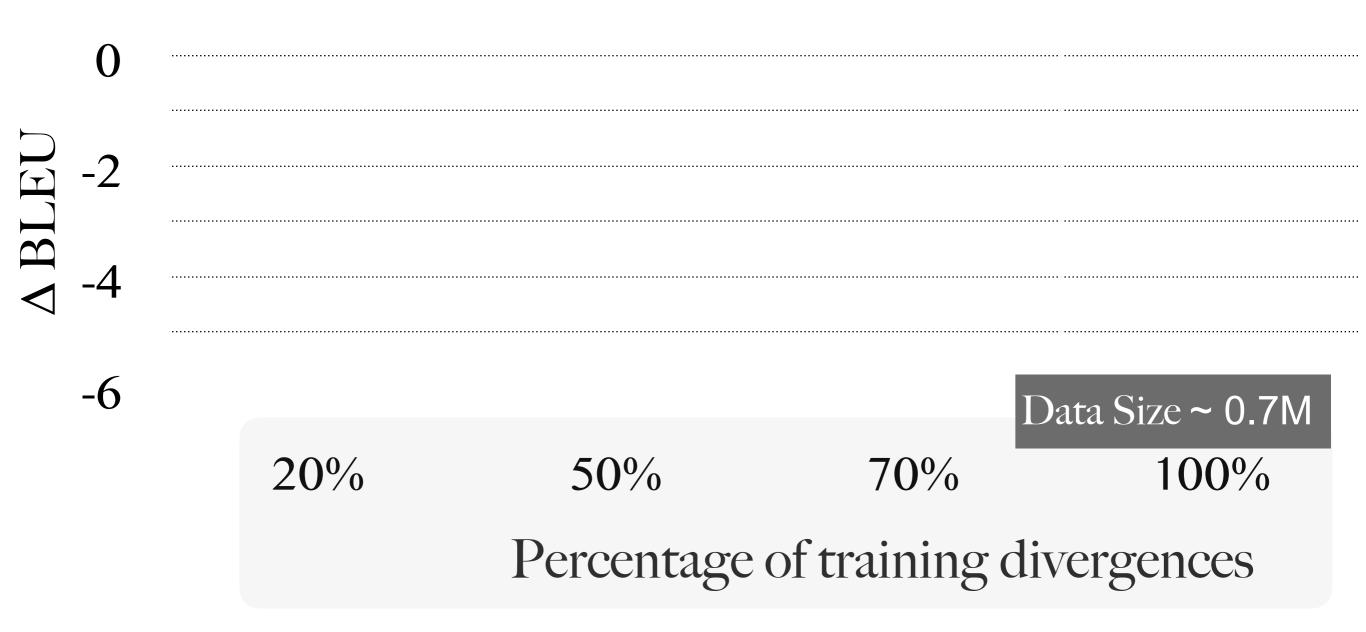
ils vous demandent votre aide they are asking

LEXICAL SUBSTITUTION

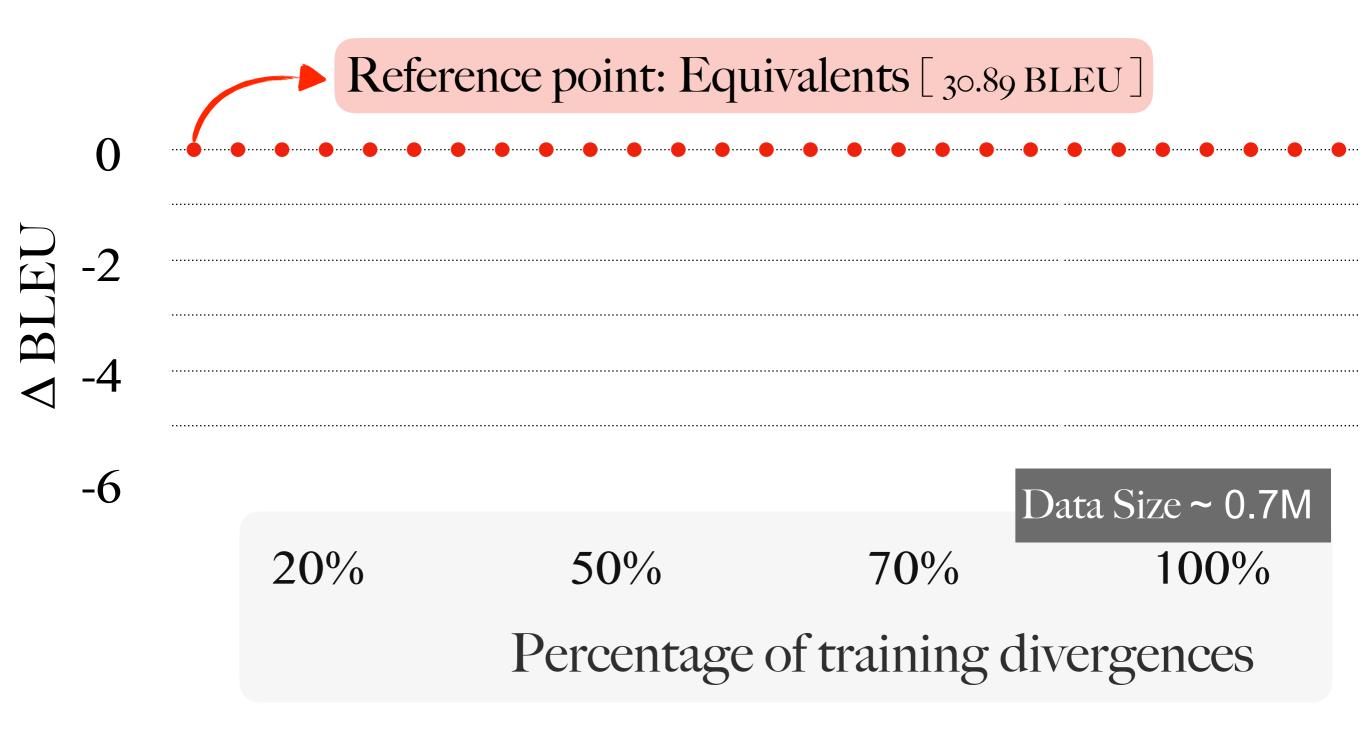
ils vous demandent votre aide they are asking your mercy



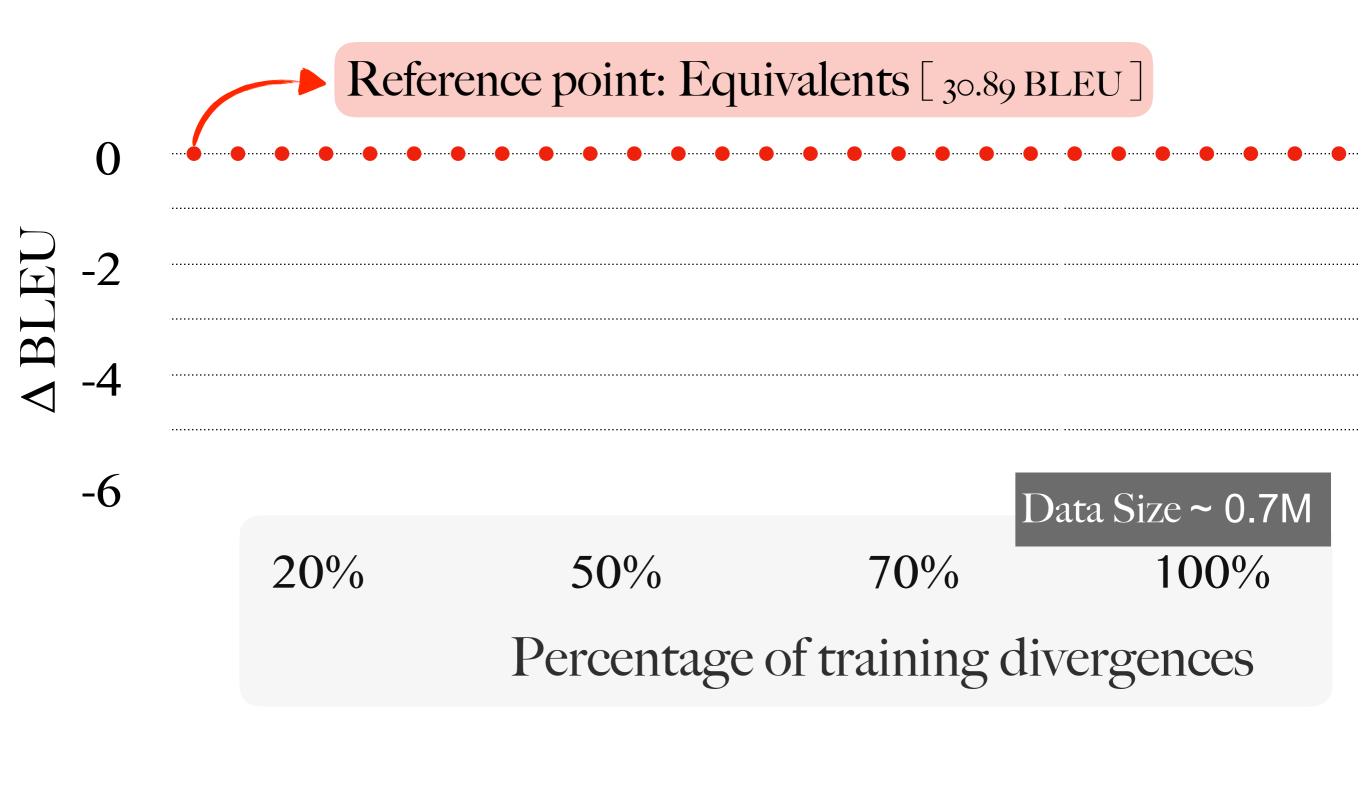
Fine-grained Divergences: Impact on BLEU



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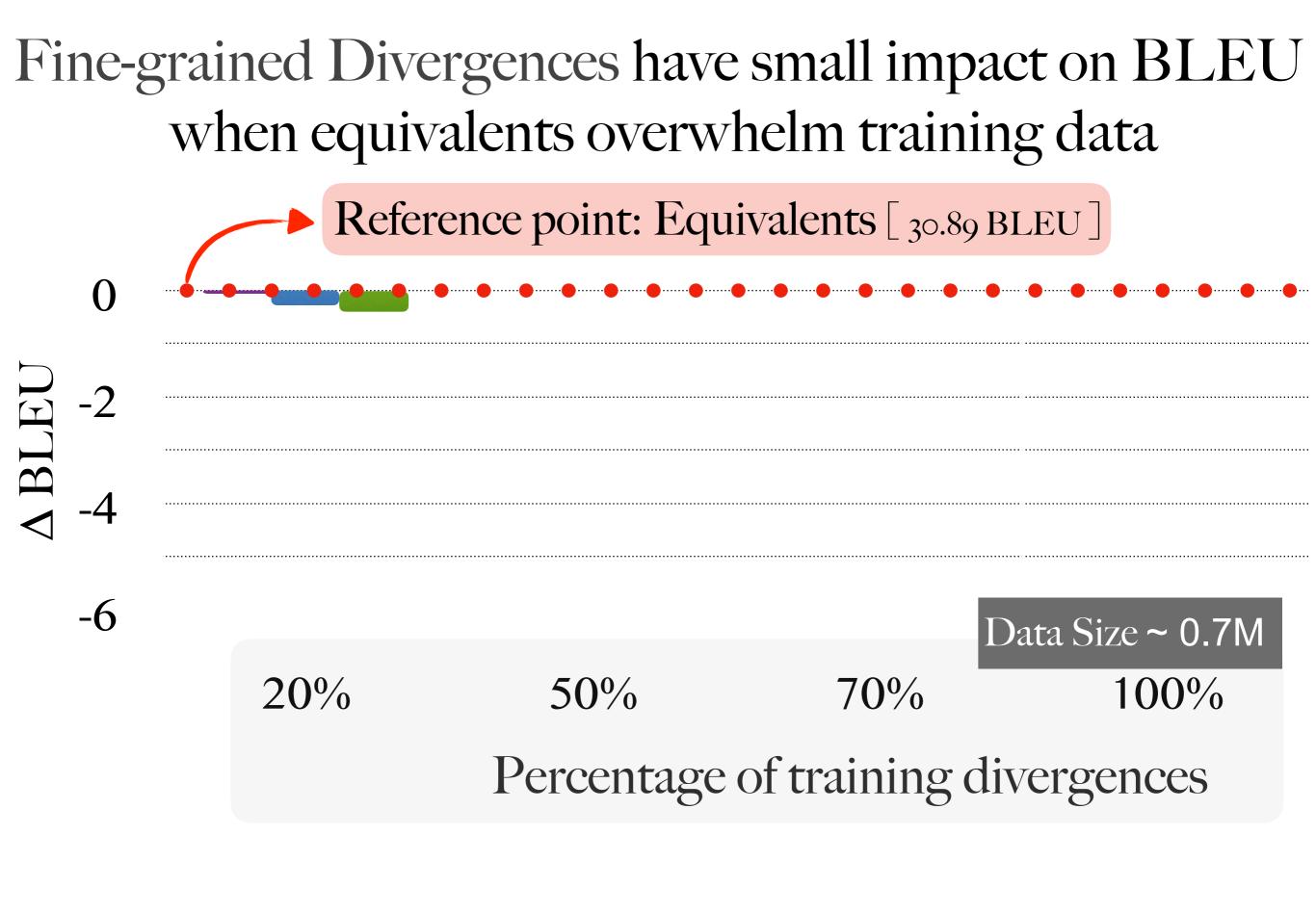
Fine-grained Divergences: Impact on BLEU



Phrase Replacement

Subtree Deletion

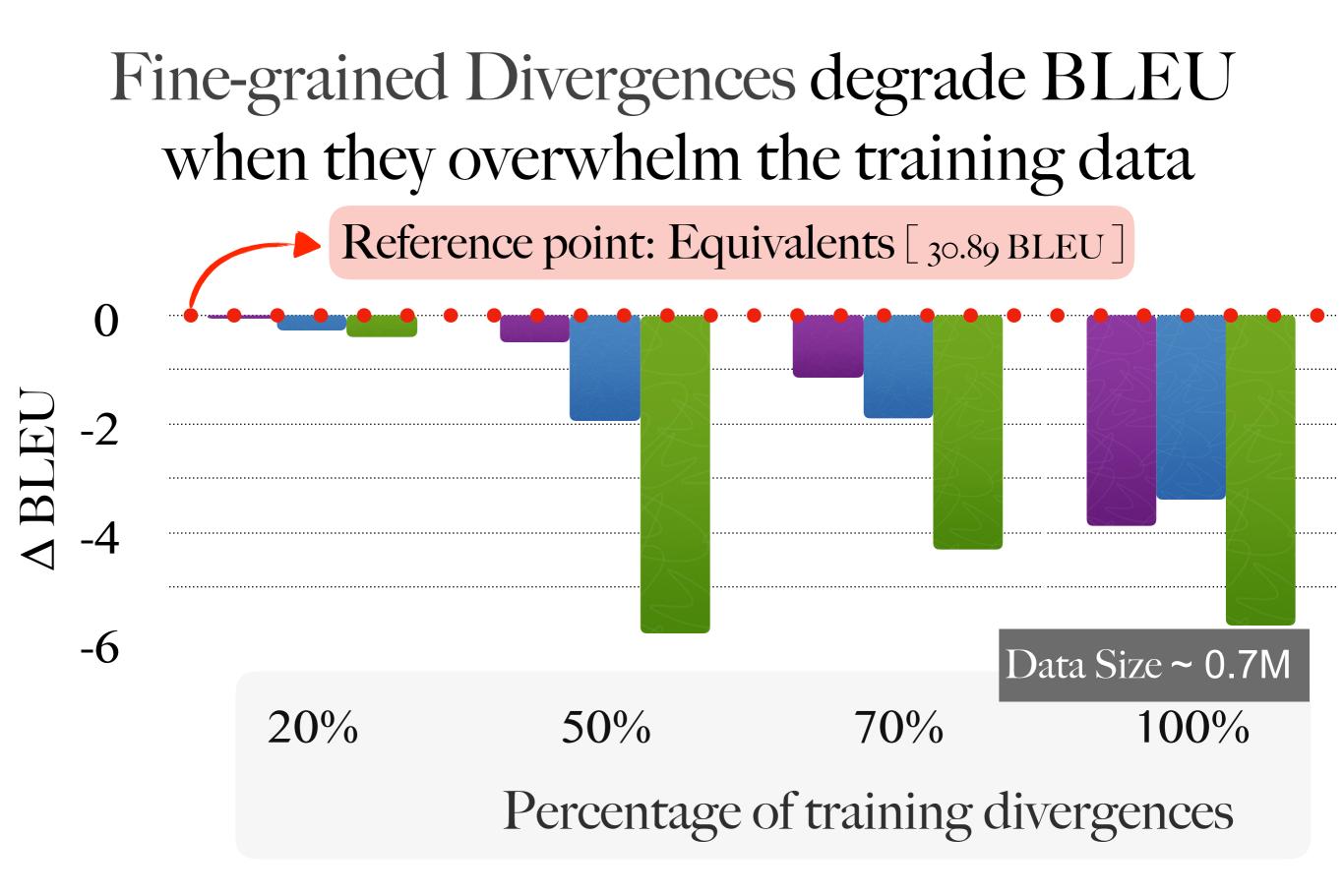
Lexical Substitution



Phrase Replacement

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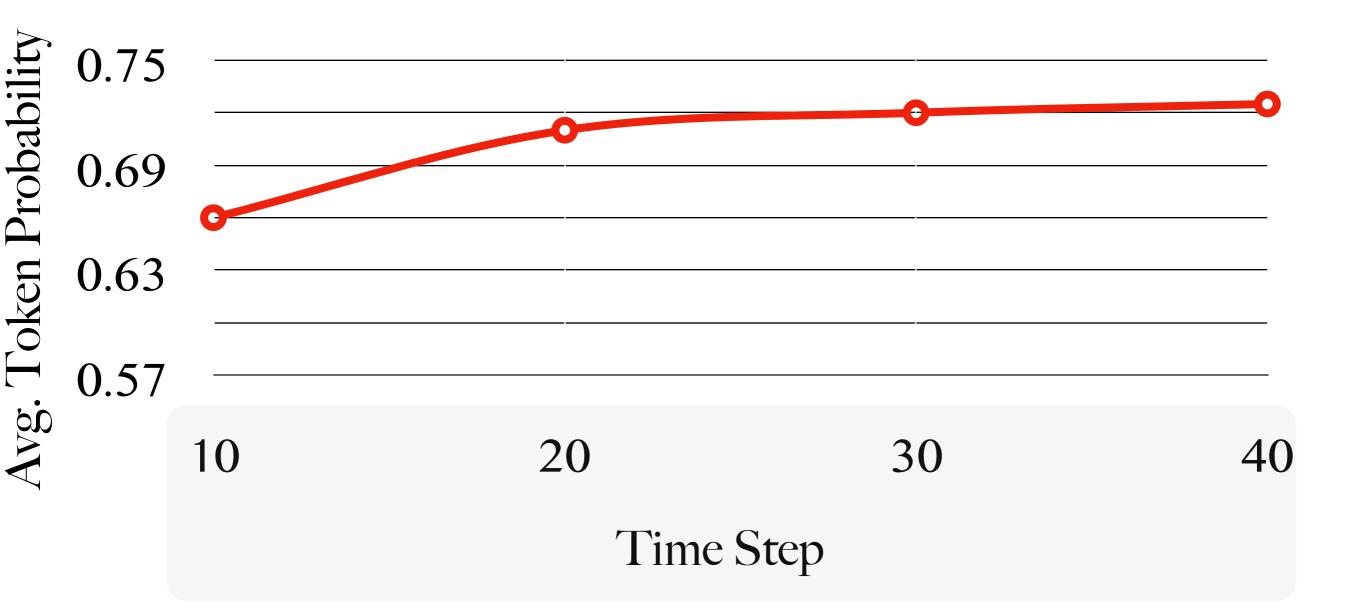
Fine-grained Divergences: Impact on uncertainty

oility	0.75				
Probability	0.69				
l'oken P	0.63				
	0.57				_
Avg.		10	20	30	40
			Time Step		

Phrase ReplacementLexical Substitution

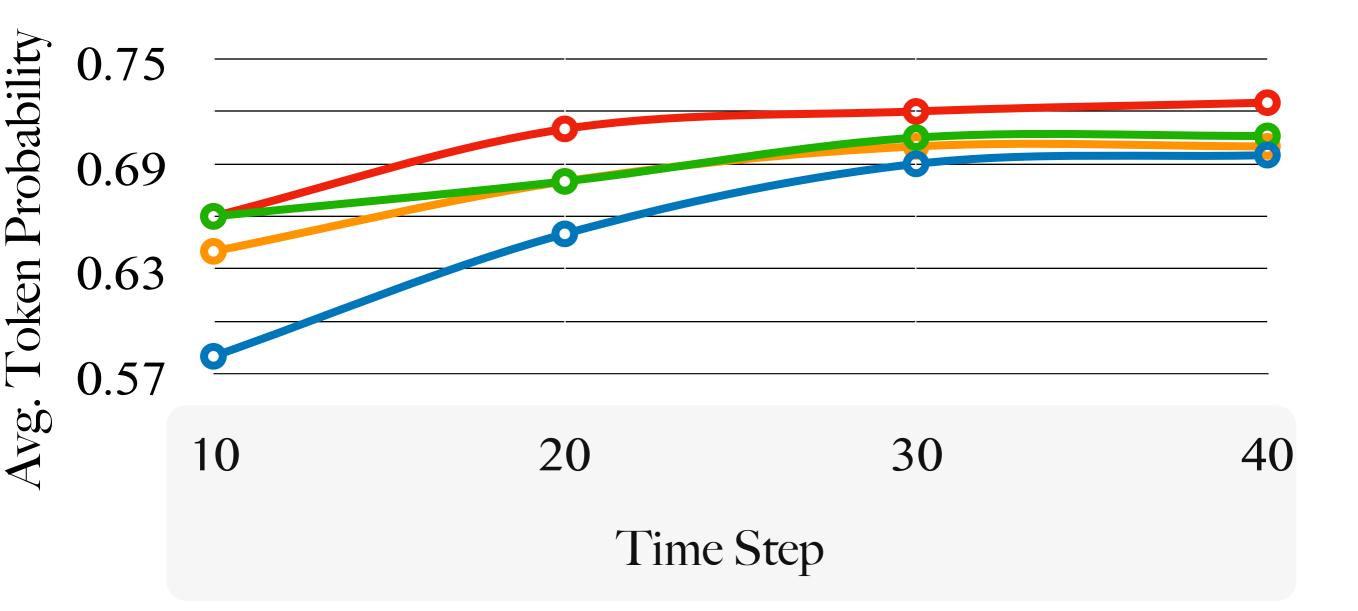
Subtree DeletionEquivalents

Fine-grained Divergences: Impact on uncertainty



Phrase ReplacementLexical Substitution

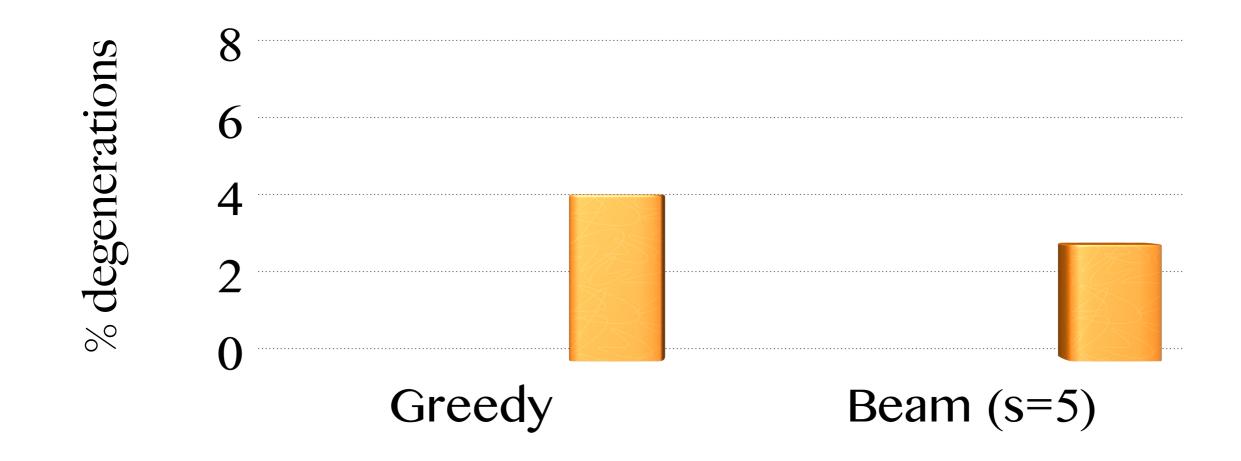
Fine-grained Divergences increase the uncertainty of token predictions



Phrase ReplacementLexical Substitution

Fine-grained Divergences: Impact on degenerated hypotheses

i.e., "I've never studied sculpture, engineering and architecture, and the engineering and architecture"

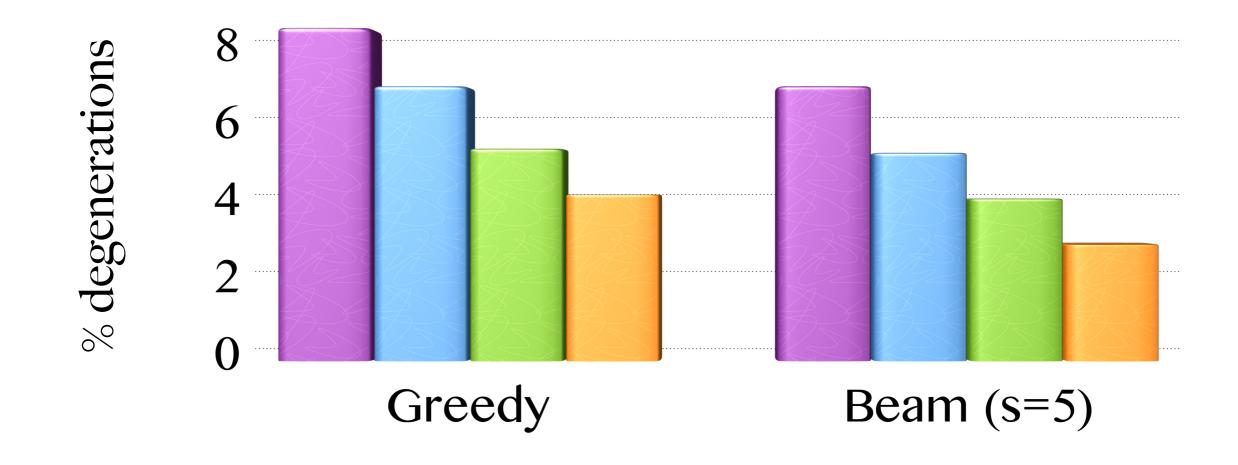






Fine-grained Divergences increase the frequency of degenerated hypotheses

i.e., "I've never studied sculpture, engineering and architecture, and the engineering and architecture"







Our work

How do fine-grained divergences impact NMT?

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How can we mitigate their negative impact?

by encoding divergences as token factors

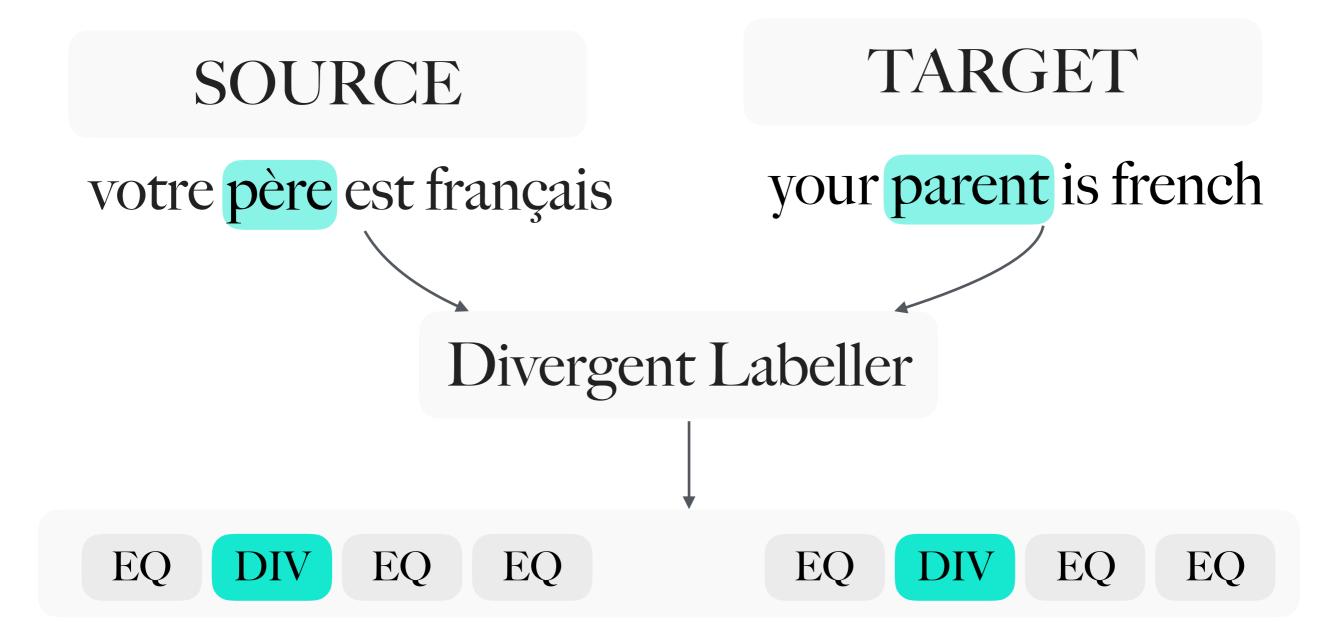
SOURCE

votre père est français

TARGET

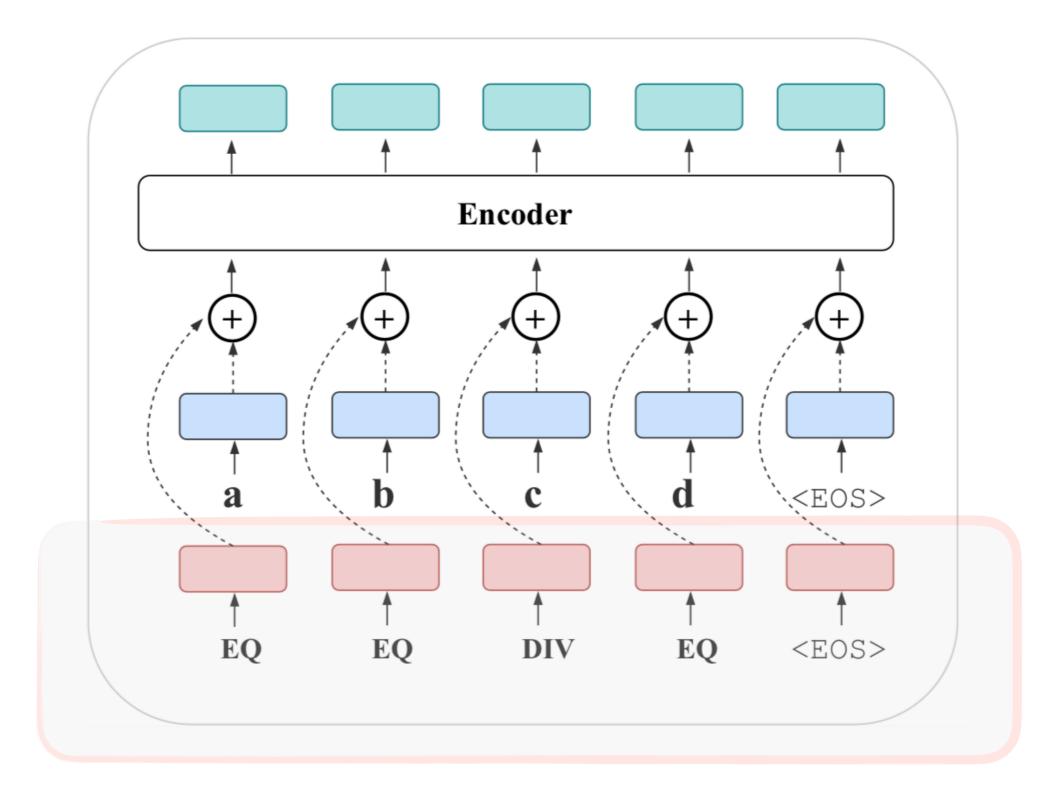
your parent is french



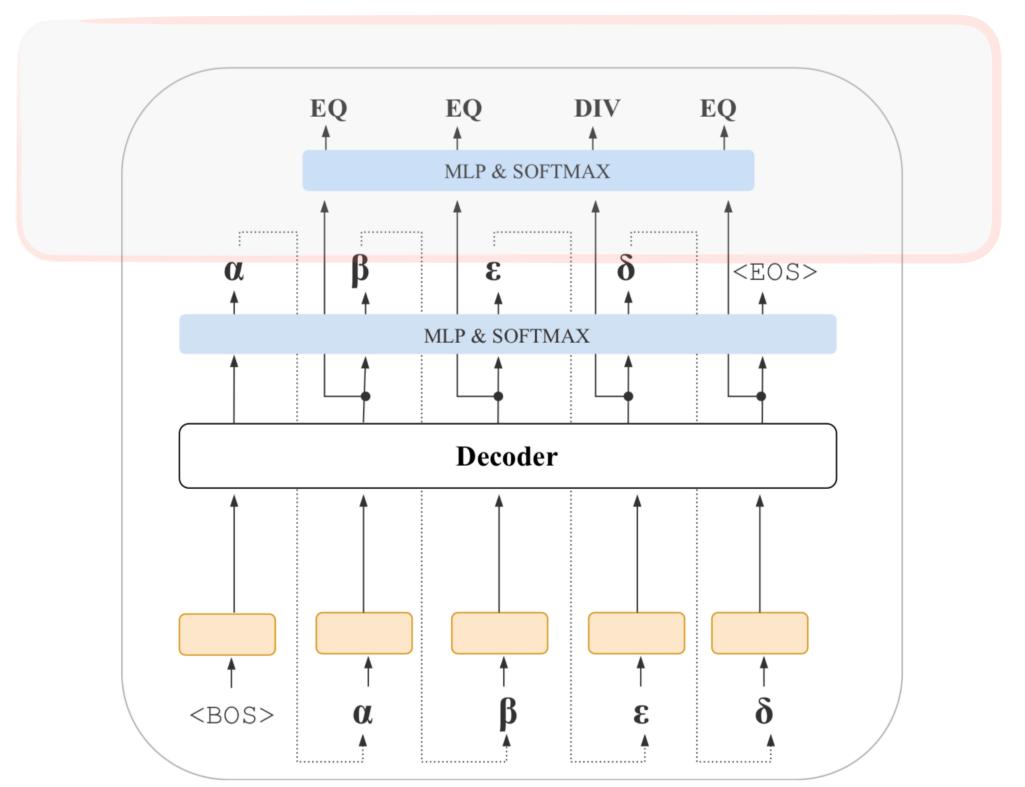


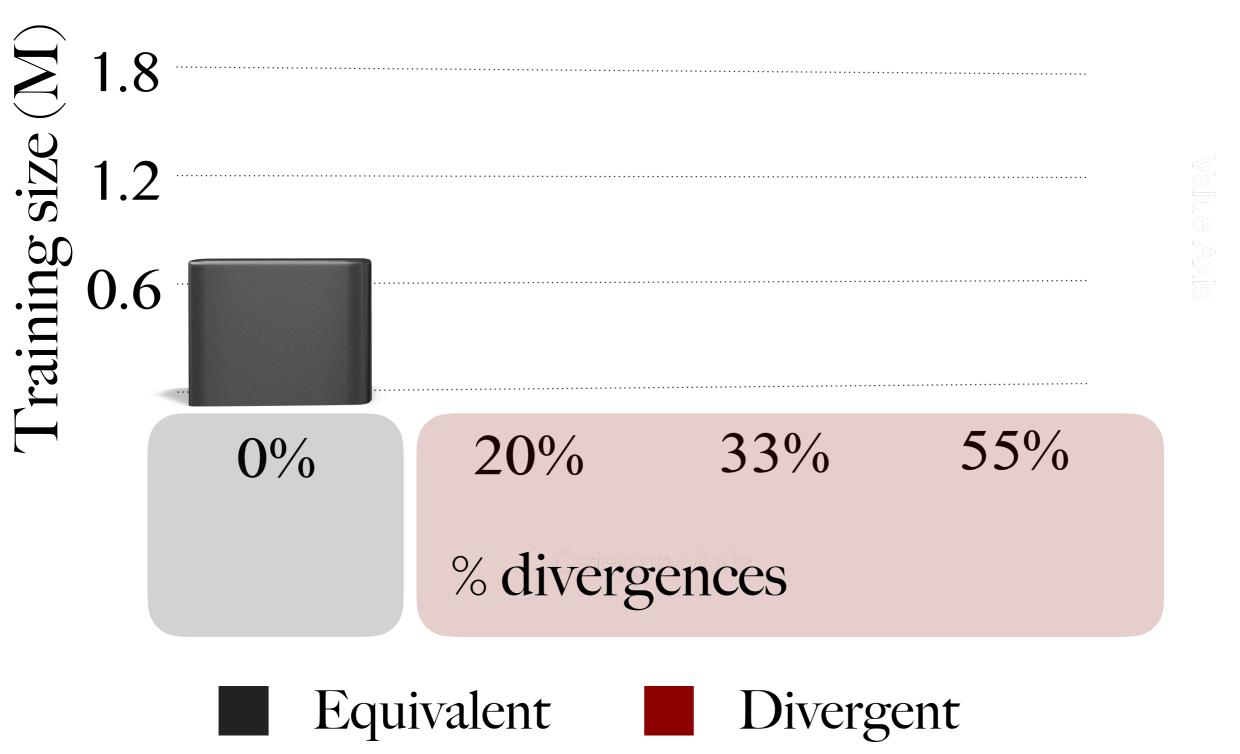


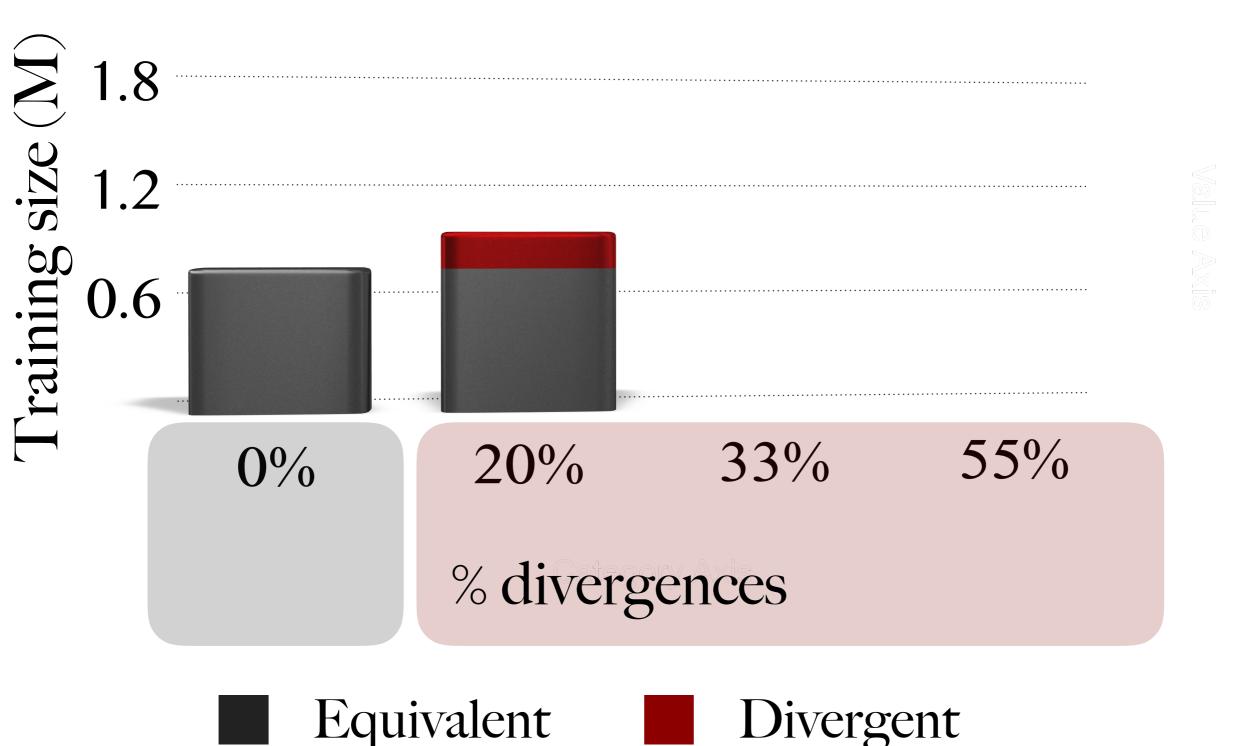
Source-side factors: divergent tags are encoded as additional features

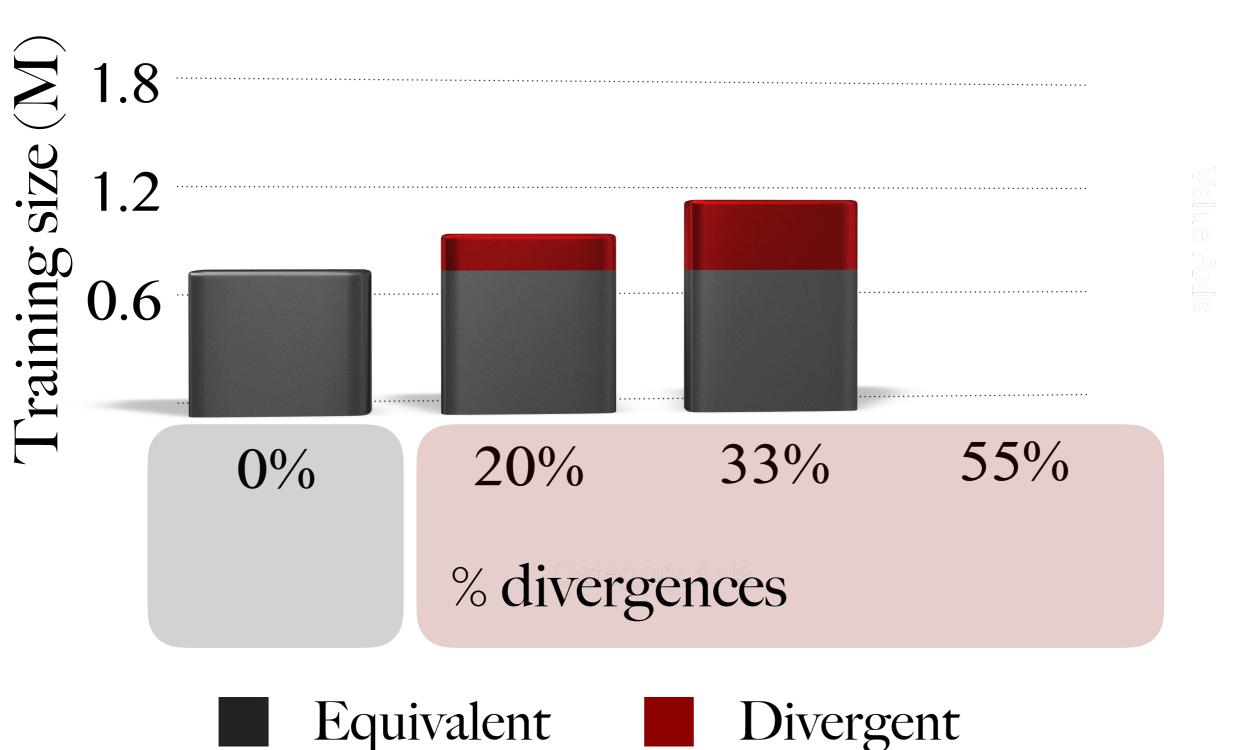


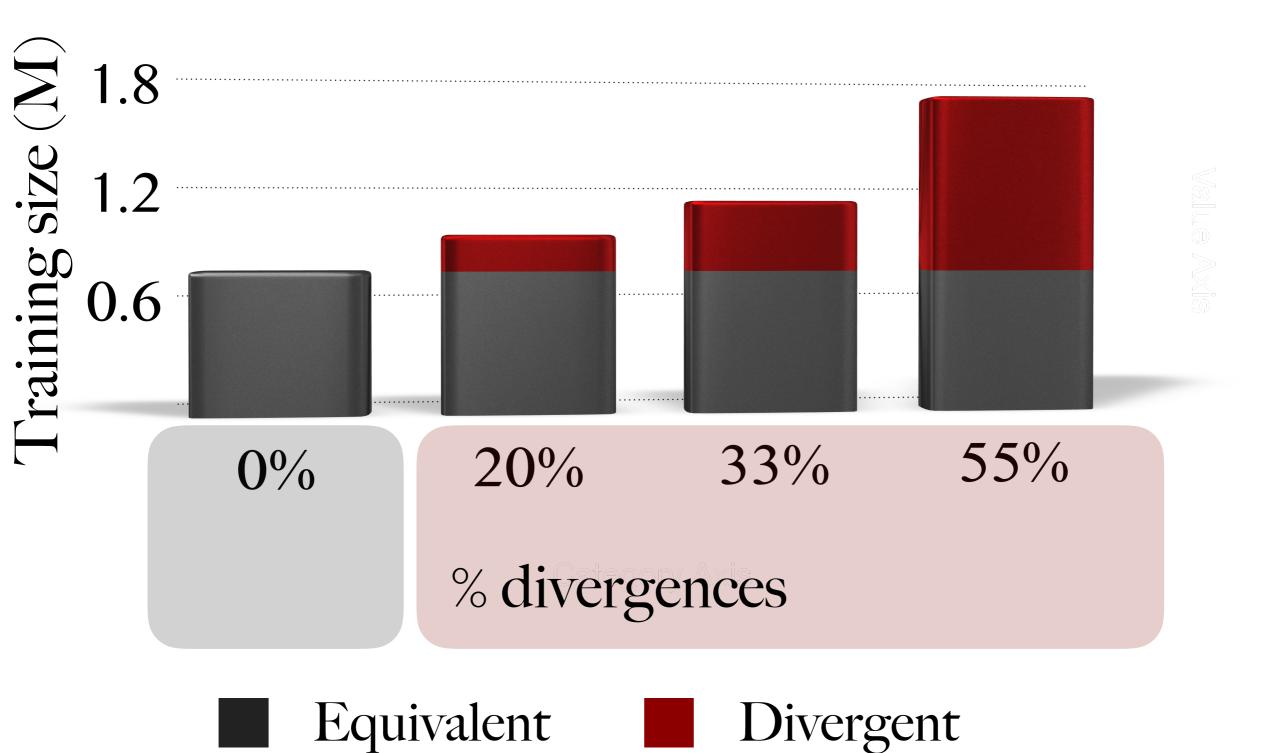
Target-side factors: divergent tags are generated additional sequence



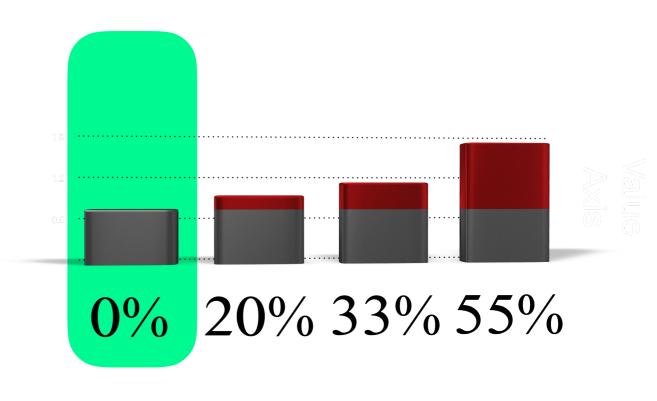






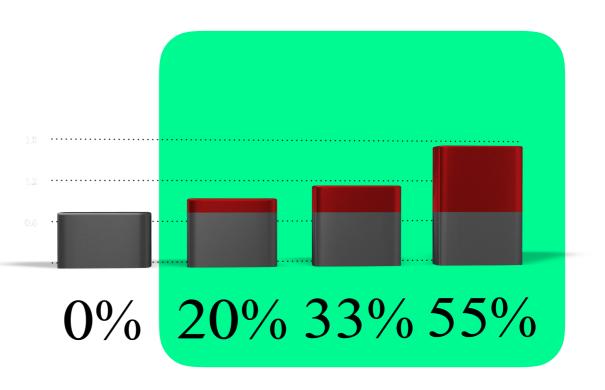


<u>Models</u> • Equivalents



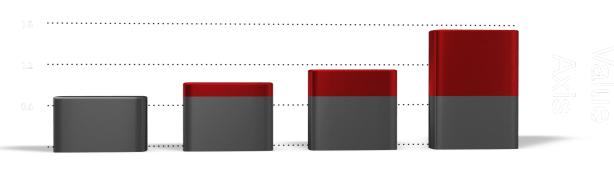
Category Axis

Models
O Equivalents
O DIV-AGNOSTIC
O DIV-FACTORS



Category Axis

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0% 20% 33% 55%

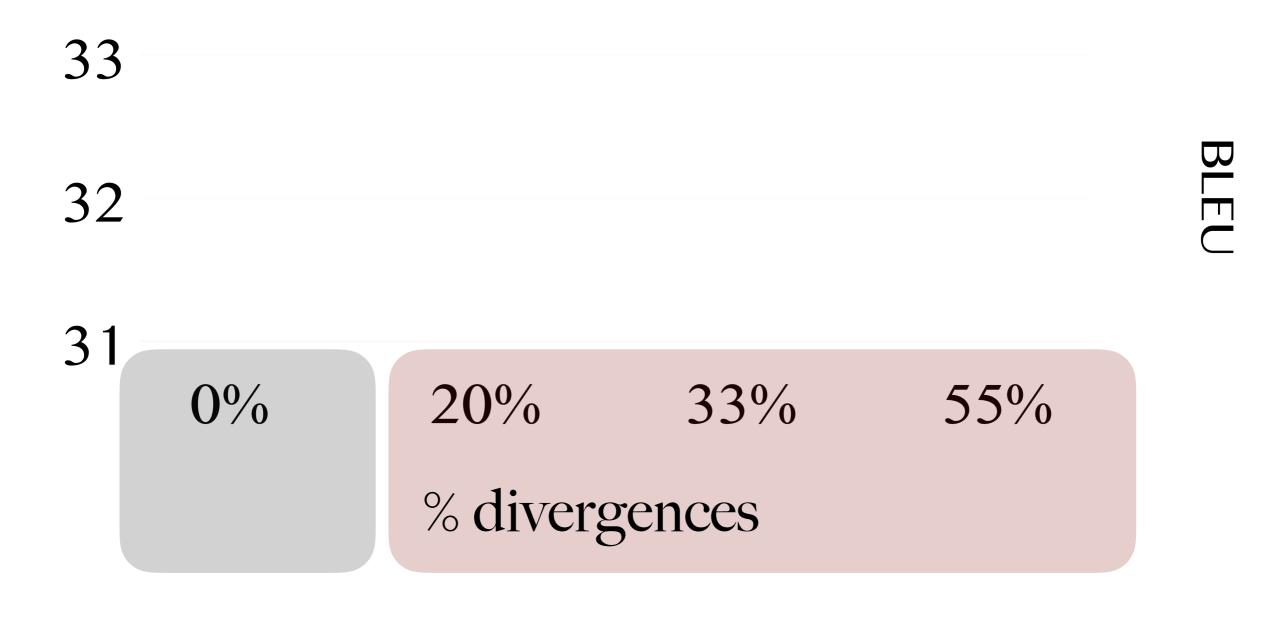
Category Axis

- : WikiMatrix (mined)
 - TED
- : French English

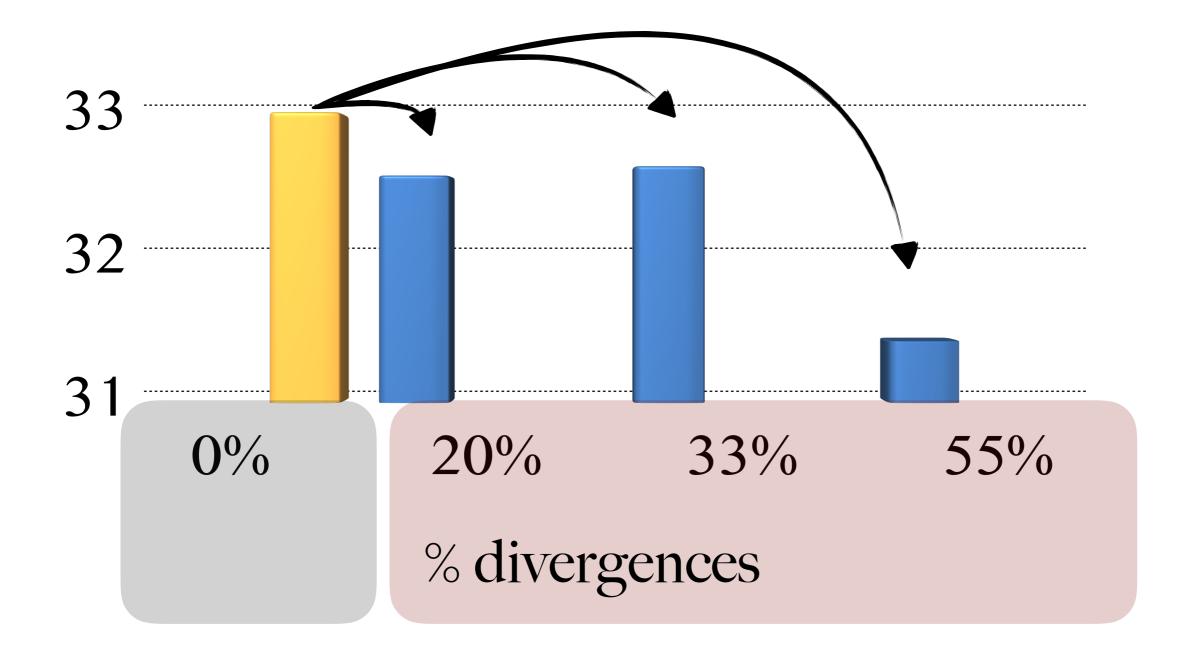
: Transformer

- Training bitext
- Test set
- Language-pair
- NMT architecture

Divergences decrease translation quality



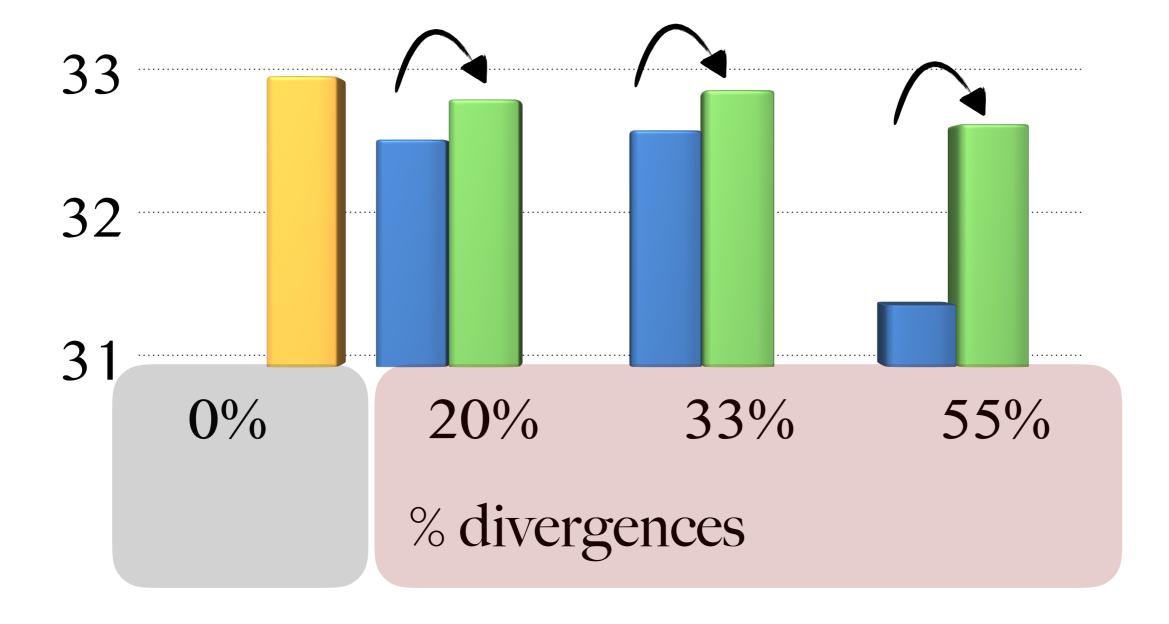
Semantic Divergences decrease translation quality



DIV-AGNOSTIC DIV-FACTORS Equivalents

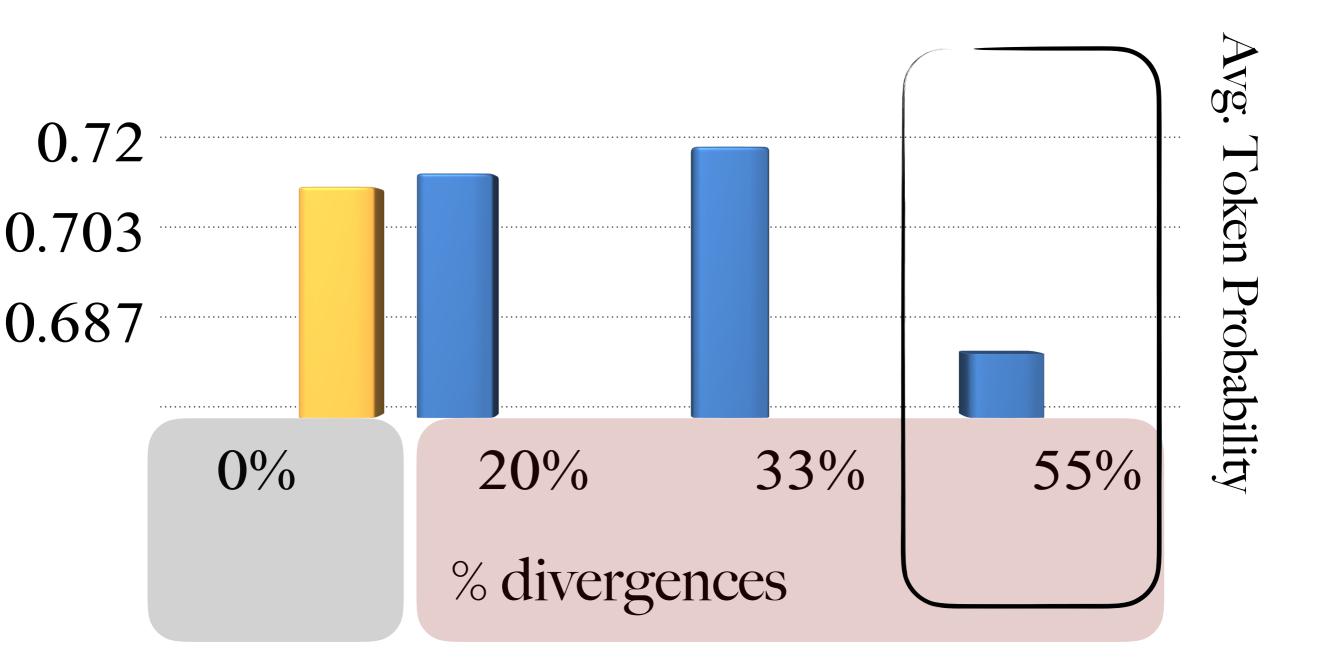
BLEU

Modeling divergences via factors help NMT recover from BLEU degradations

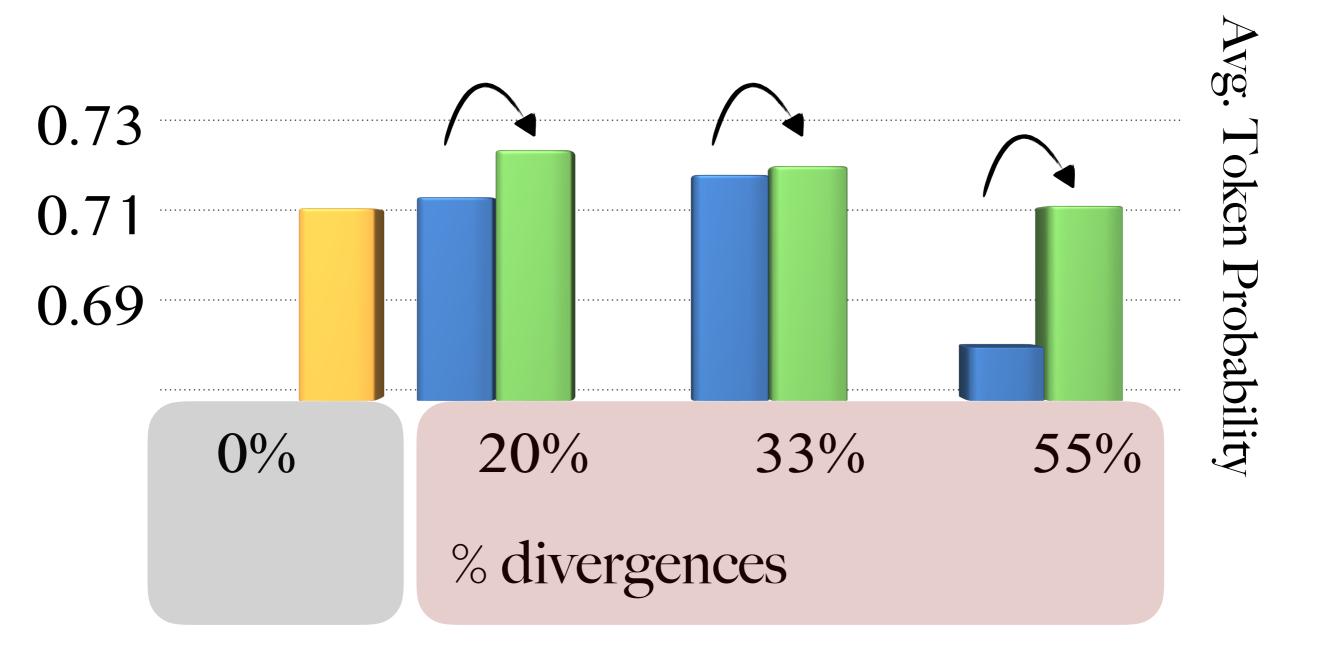


BLEU

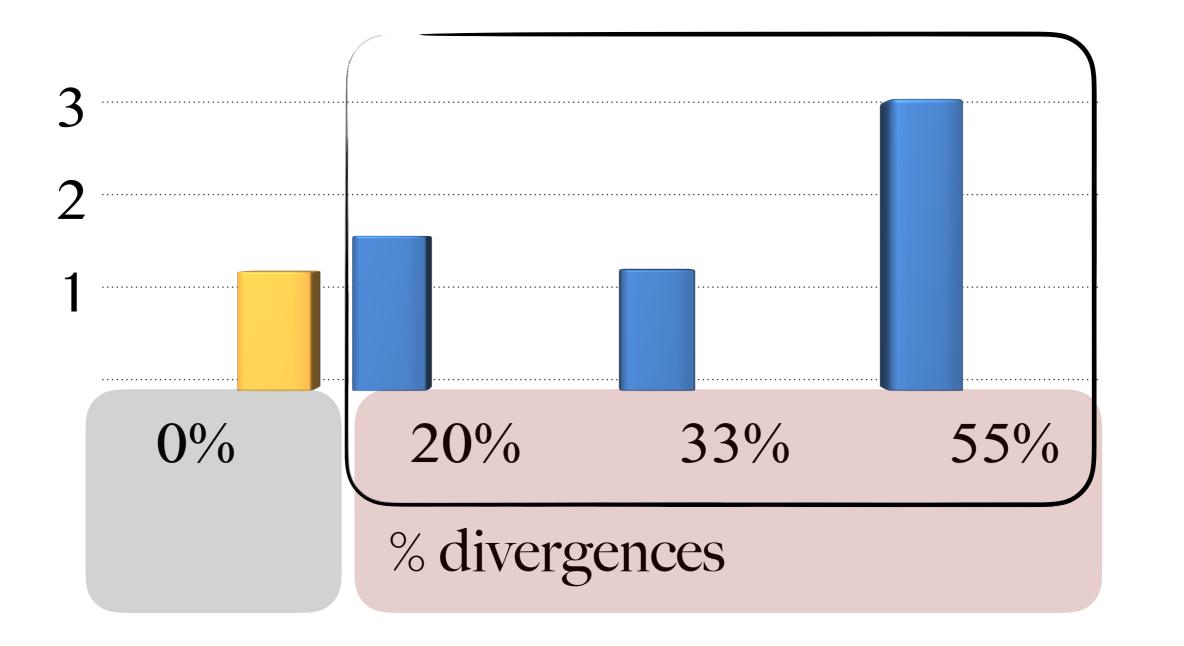
Semantic Divergences decrease the confidence of token predictions



Modeling divergences via factors mitigate their negative impact on models' confidence

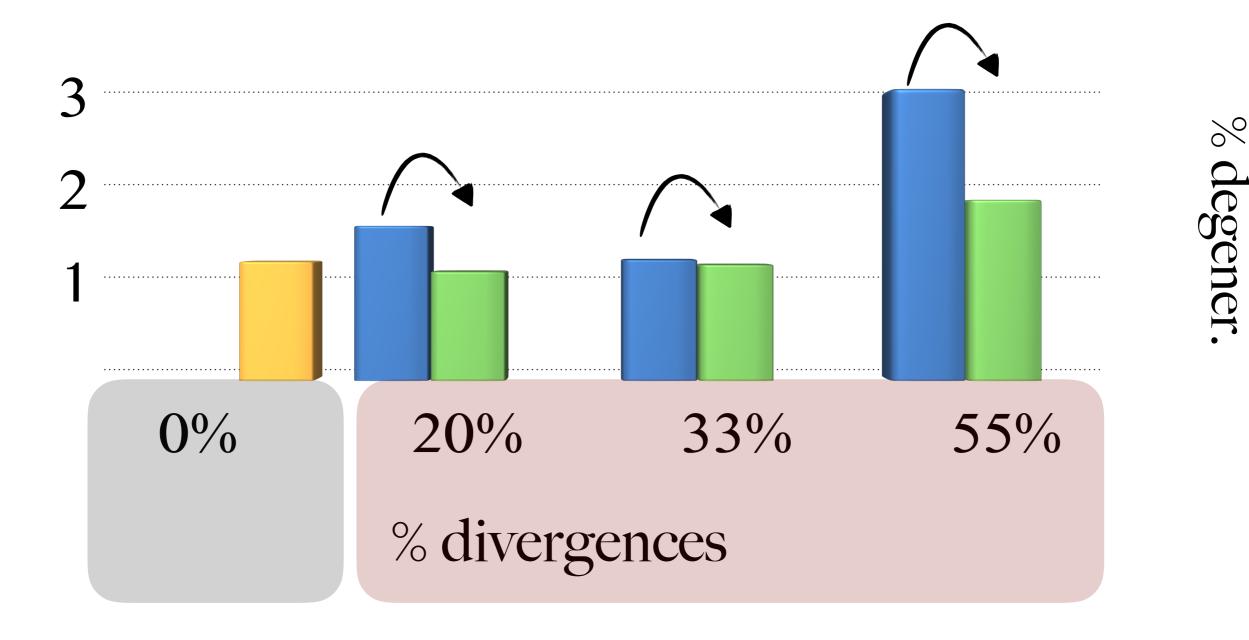


Semantic Divergences increase the frequency of degenerations



% degener.

Modeling semantic divergences via factors yield fewer degenerations



Take-aways: Fine-grained distinctions...

impact various aspects of NMT
 when they overwhelm the training data
 hurt translation quality
 more repetitive loops

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O https://github.com/Elbria/xling-SemDiv-NMT