AMTA VIRTUAL 2020

The 14th Conference of
The Association for Machine Translation
in the Americas

www.amtaweb.org

WORKSHOP PROCEEDING

Workshop on the Impact of Machine Translation

Organizers:
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Michel Simard (National Research Council Canada)

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AMPLEXOR
EMBRACE THE FUTURE


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The Machine is Blind
Bottom-Up Feedback on the Impact of MT on Human Translation Performance
RHETT WHITAKER
OCTOBER 6, 2020

A Brief Overview

- Blind spots and information flow
- What do translators really think of MT?
- The challenge facing translators
- Impacts in the short and long term
- Recommendations

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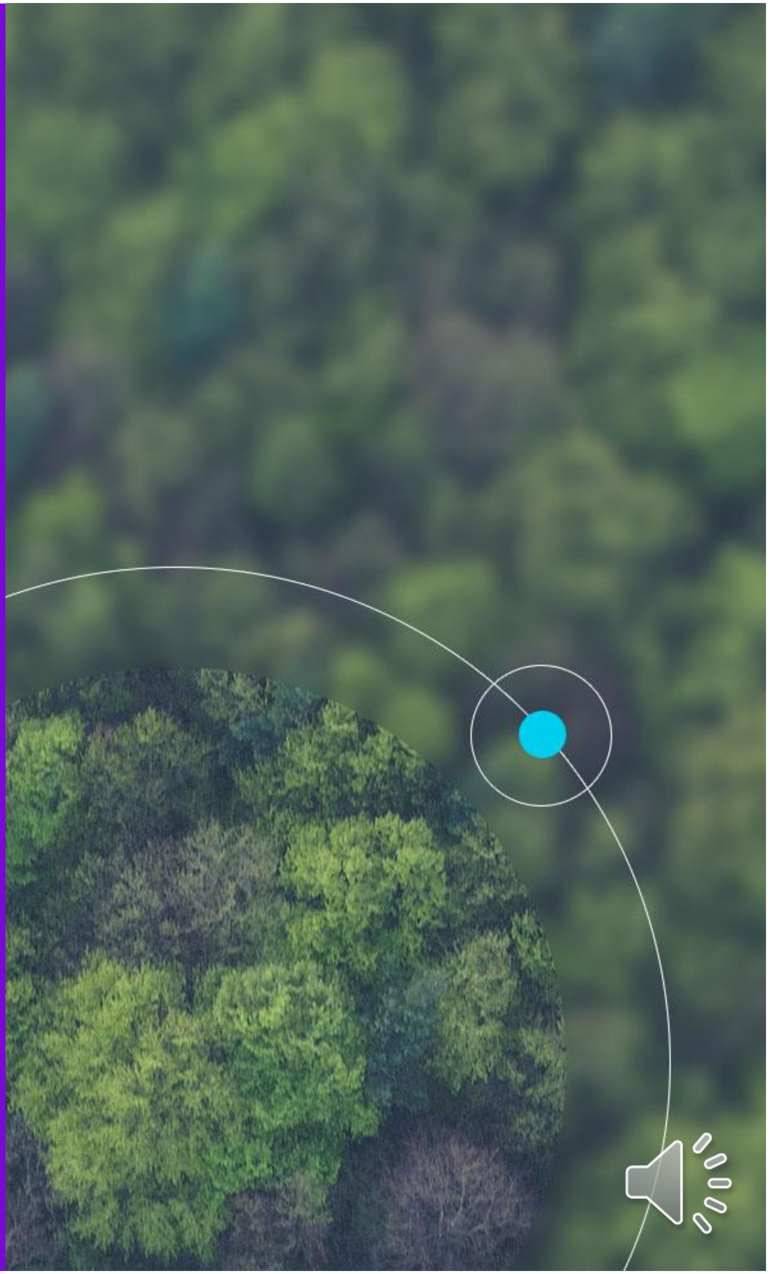
Blind Spots and Information Flow



Know How Your Information Flows

Downstream

Upstream

Decision-makers

Executives and upper management

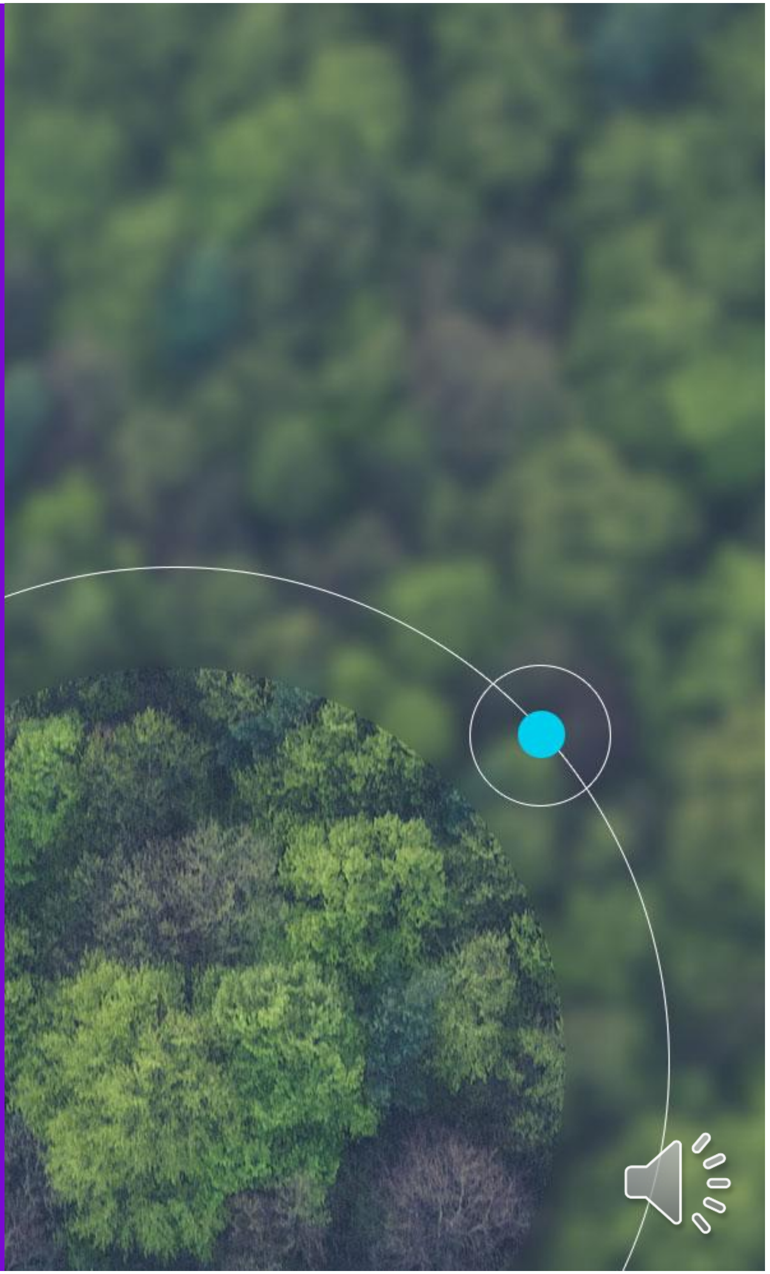
Facilitators

Middle management, service coordinators, project managers

Production

Translators, editors, and other linguists

What Do Translators Really Think of MT?



Positive feedback

"MT frees me up for other, more valuable tasks."

7

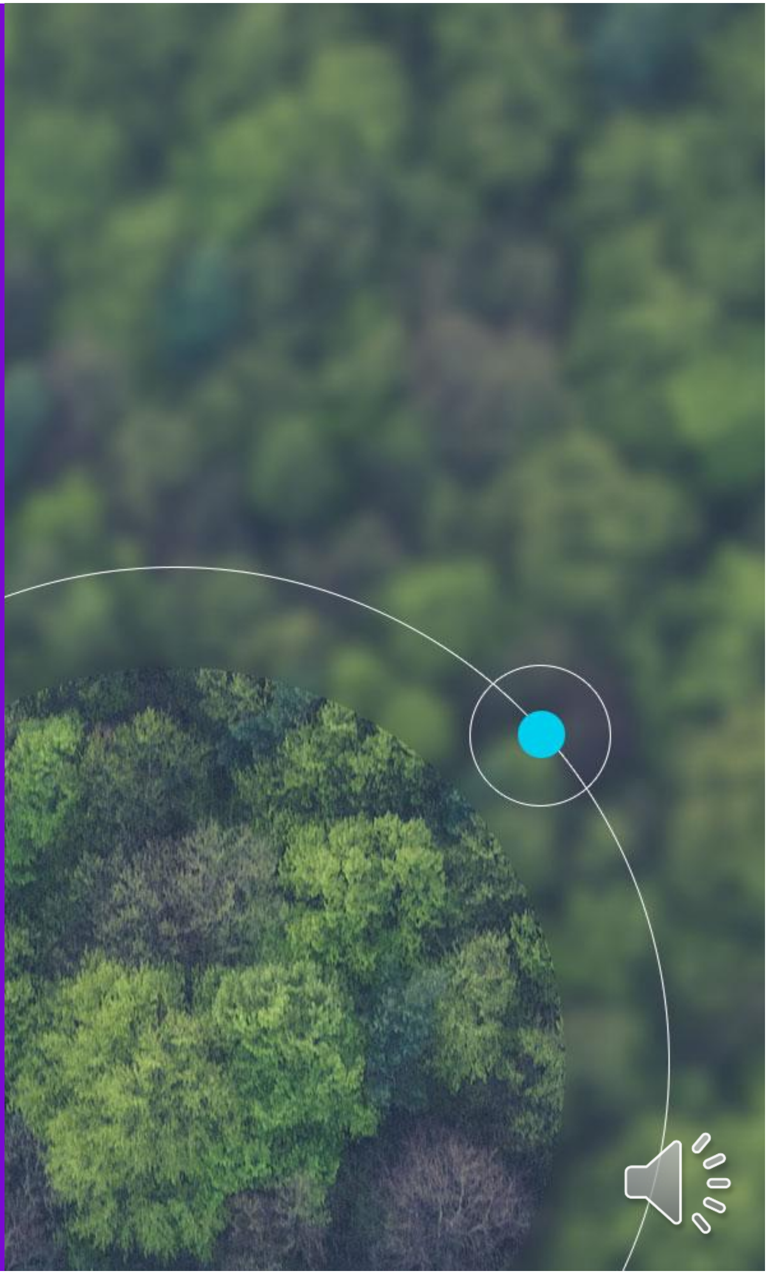
Negative feedback

"This is more work than translating from scratch."

"I don't know why it's making these errors."

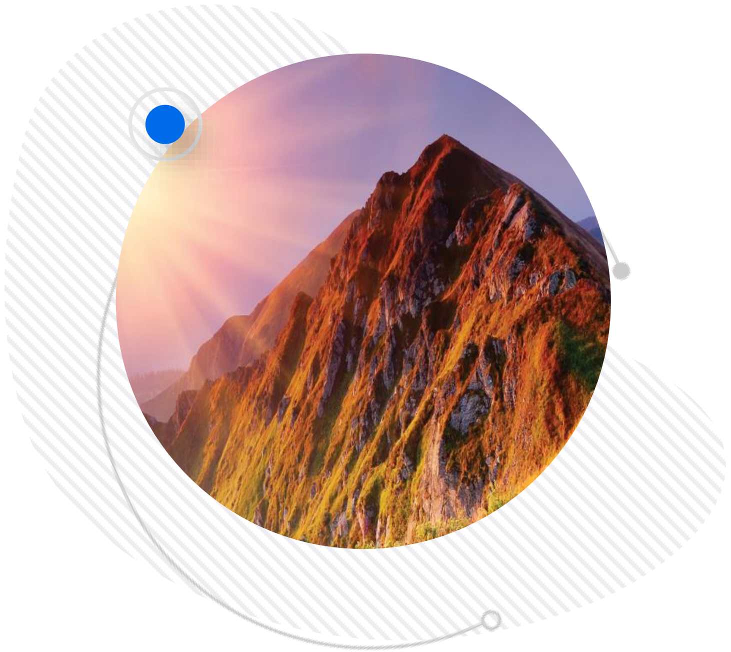
8

The Challenge Facing Translators



A Challenging Situation

TRANSLATORS BETWEEN A ROCK AND A HARD PLACE



LESS PAY

LSPs tend to prorate what they pay for MT post-editing services, sometimes to a significant degree.

MORE WORK

In particular, high-quality translators view poorly implemented MT as a hindrance to their work.

MORE TEDIOUS

Long intervals between retraining MT engines can lead to frustration on the translator's part.

DEAF EARS

Bottom-up feedback that is ignored can act as a significant demotivating force.

"Is this kind of work still worth doing?"

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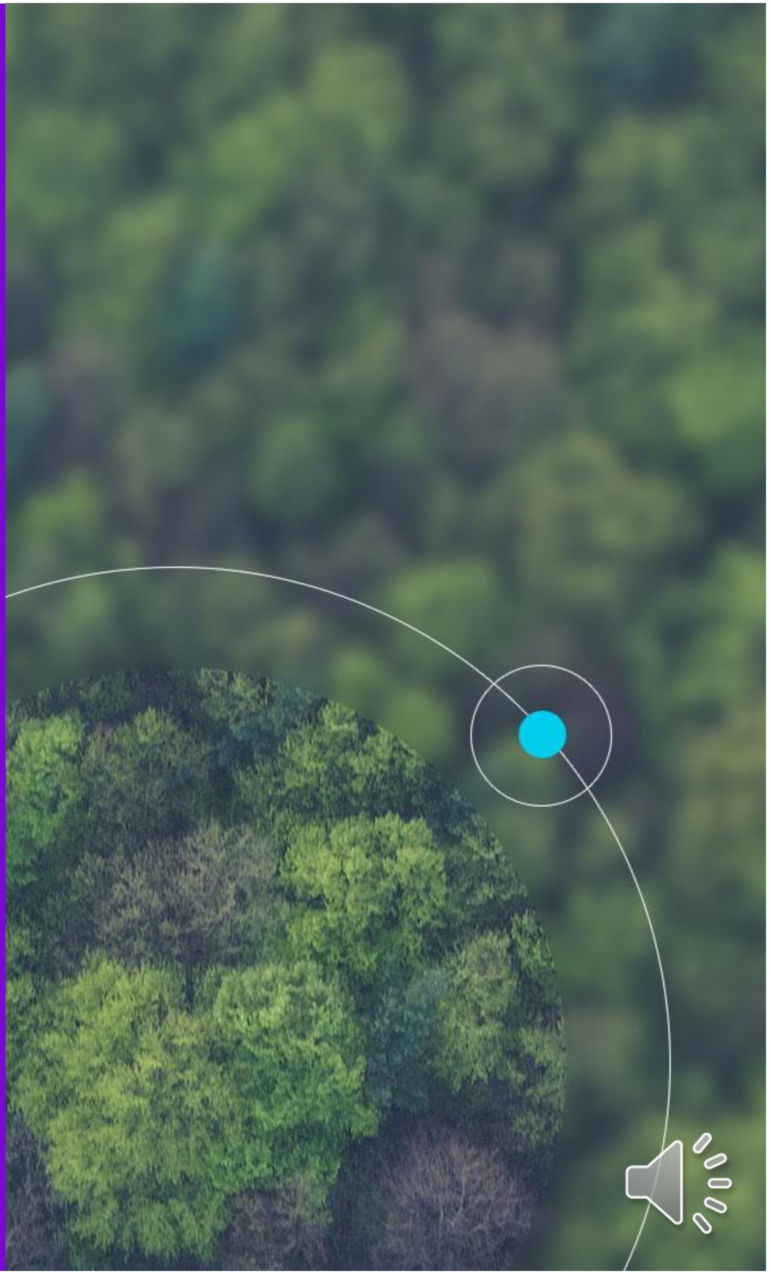
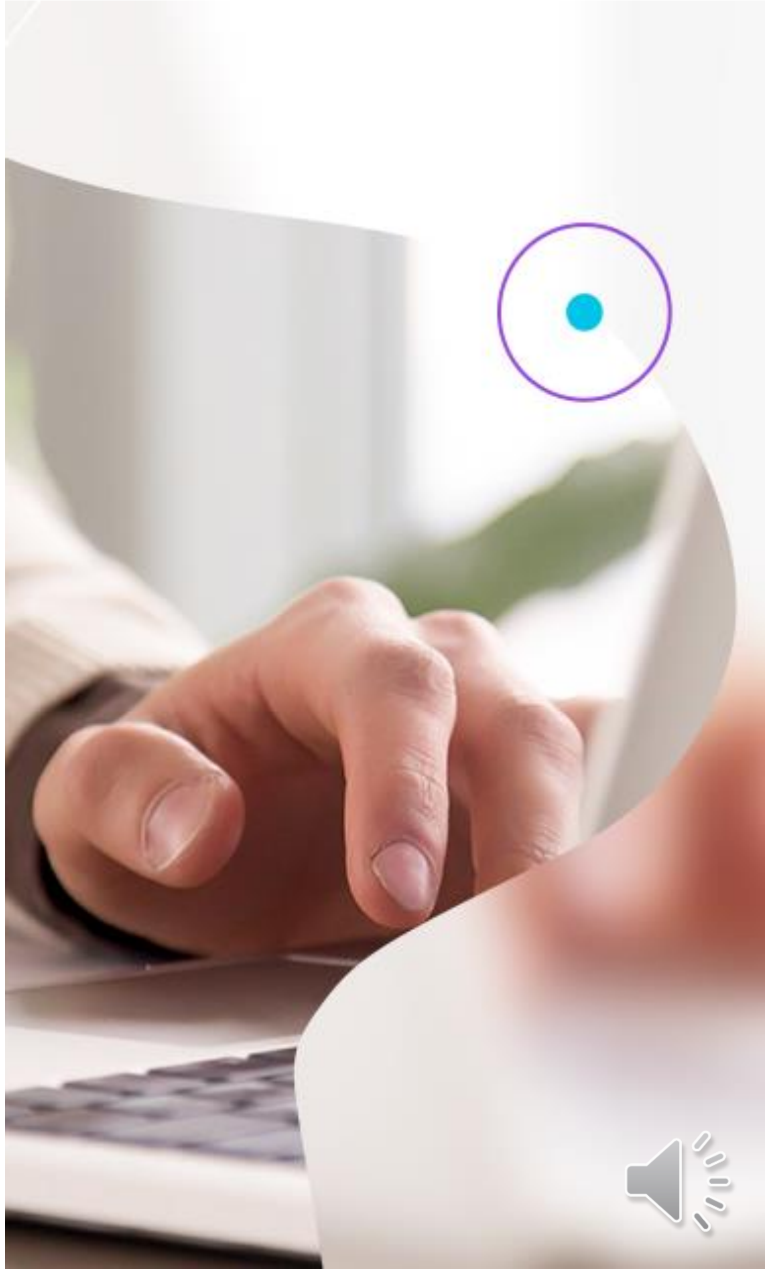
Impacts in the Short and Long Term



Short term

Translators dealing with poorly implemented MT are often unfocused, unmotivated, and less effective. This could produce the following short term impacts:

- Translators increasingly reject MT post-editing jobs
- Translators raise rates to compensate for prorated pay
- Organizations see declining quality, similar overall costs, and diminished capacity

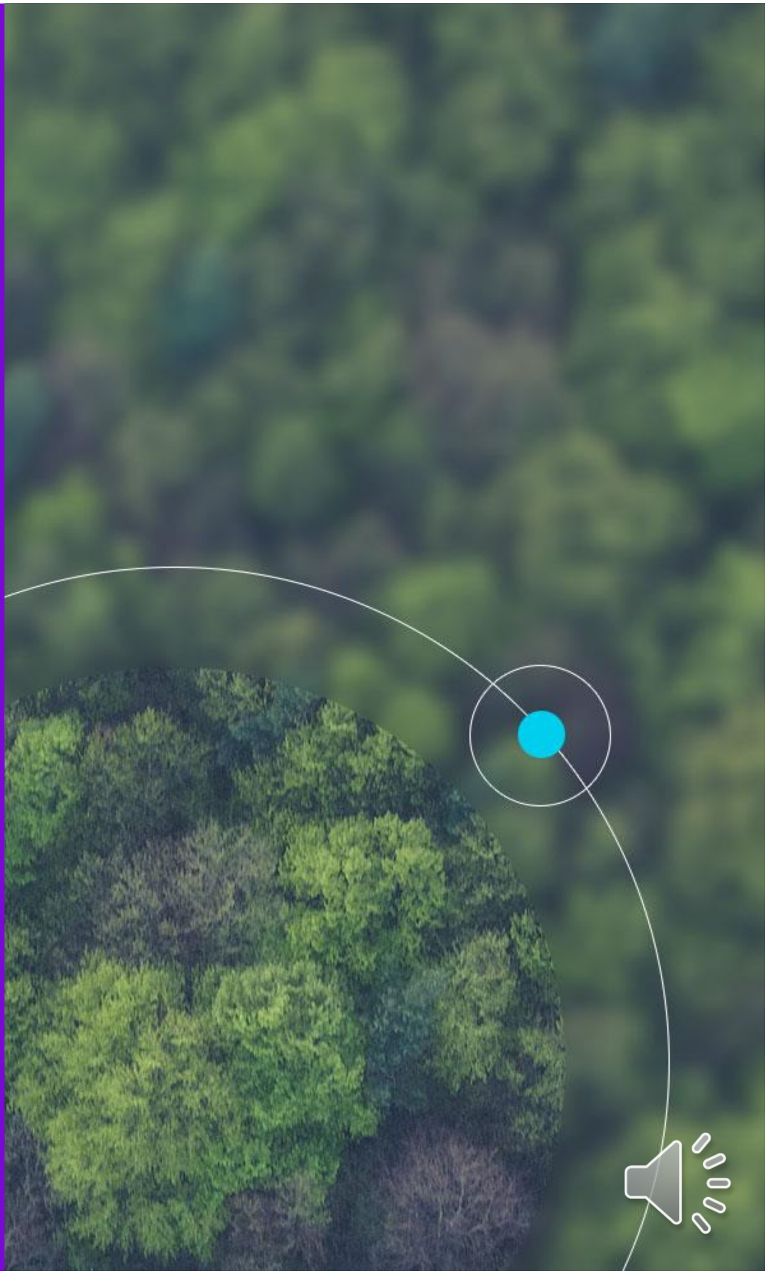


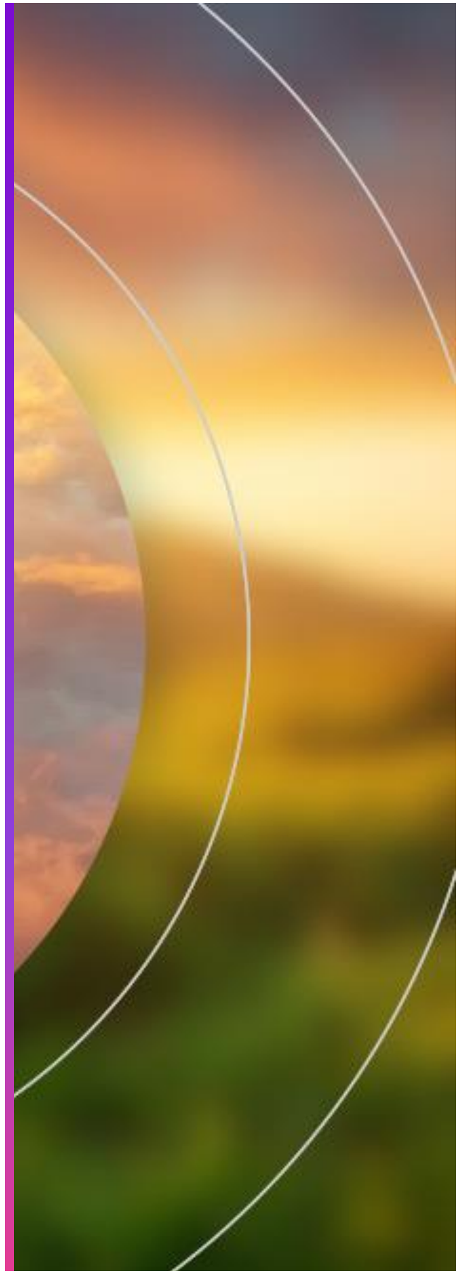
Long term

Sustained negative attitudes toward MT and frustration with the post-editing process can be a serious demotivating force for translators. This can produce the following long term impacts:

- Translators leave the talent pool permanently
- The availability of highly-skilled professionals drops below critical thresholds
- Organizations face serious challenges to profitability and ultimately an existential threat

Recommendations





Countermeasures

KEEPING YOUR EYES OPEN

Be diligent in implementing MT

Give yourself the best chance for successful MT integration and translator retention. Don't rush implementation.

Don't reduce rates prematurely

Make sure your translators are fully on board with the concept of MT before you think about adjusting their pay.

Establish upstream feedback channels

You can't react to outcomes you don't know about. Take measures to acquire reliable, actionable information.

Act on upstream feedback

Use feedback to improve your MT systems and processes. It can help keep translators at the top of their game and bolster profitability.

Thank You

We help customers manage their content and customer touchpoints to improve efficiency, increase revenue, reduce time to market and ensure quality and compliance.

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EMBRACE THE FUTURE

Responsible Gist MT Use in the Age of Neural MT

Marianna J. Martindale, iSchool PhD Candidate

University of Maryland, College Park

Also: Computational Linguist, Center for Applied Machine Translation, USG

OBLIGATORY DISCLAIMER: Opinions in this talk are my own and not necessarily those of any part of the U.S. Government

1

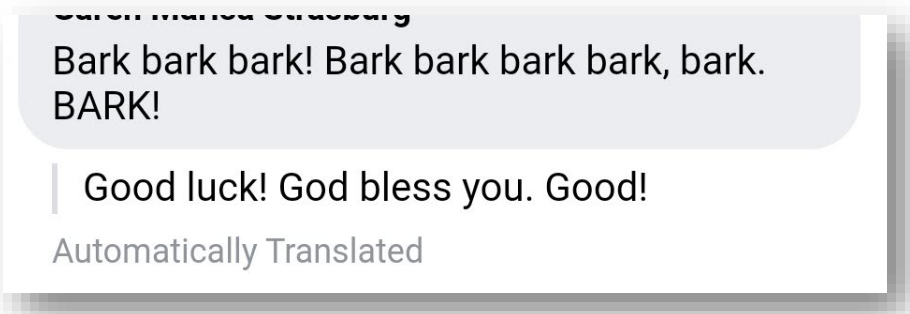
What Makes Neural MT (NMT) Different?

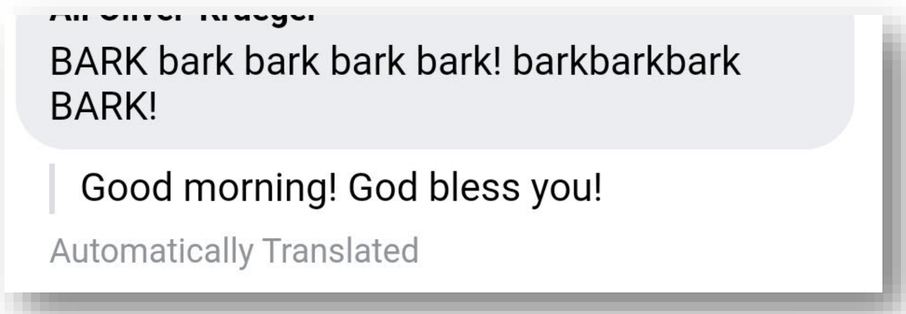
- Scores well on automated metrics & human evaluations
- Improves many types of errors (especially fluency)
- More languages & platforms than ever

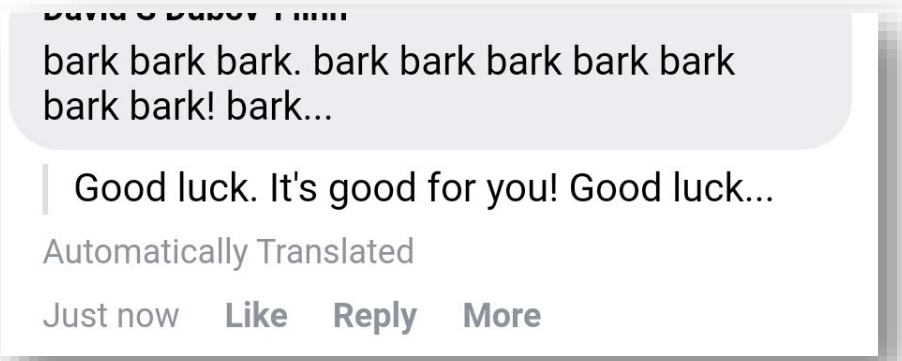
But…

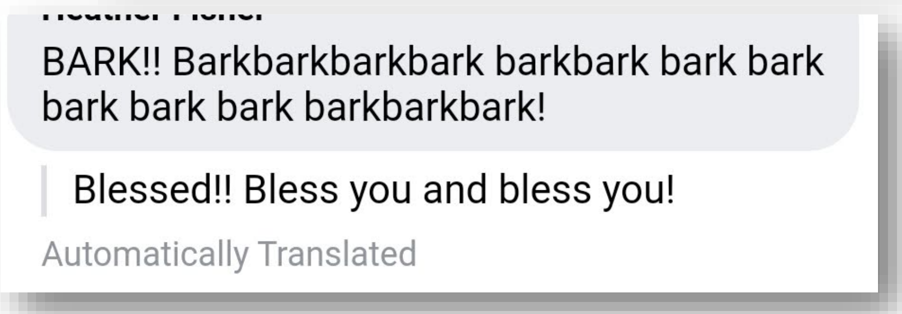
Sometimes fails catastrophically

Humorous Catastrophic Failures









Facebook, 29 April 2020

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(Semi-)Humorous Catastrophic Failures

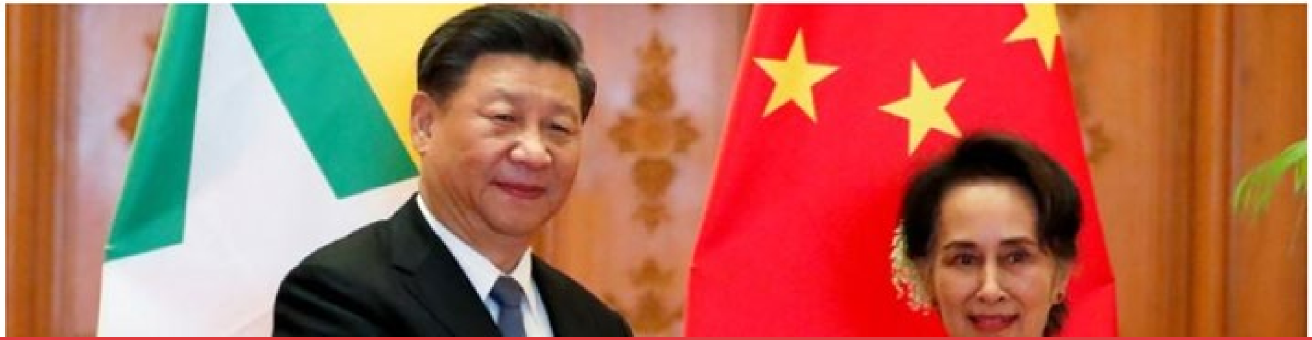
REUTERS

INTERNET NEWS JANUARY 18, 2020 / 12:27 PM / UPDATED 8 MONTHS AGO

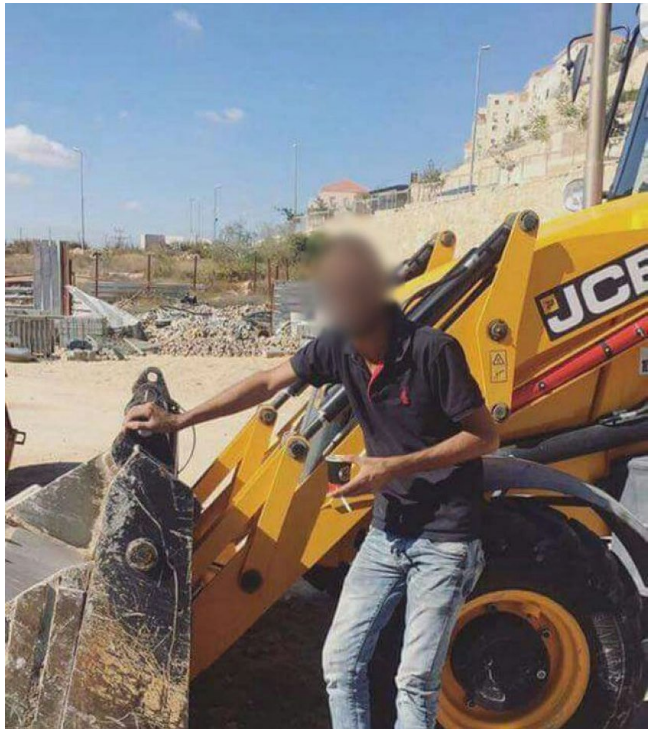
Facebook says technical error caused vulgar translation of Chinese leader's name

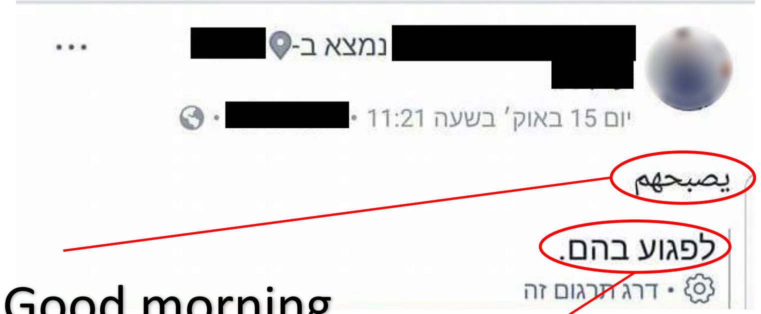
By Poppy McPherson 3 MIN READ

YANGON (Reuters) - Facebook Inc FB.O on Saturday blamed a technical error for Chinese leader Xi Jinping's name appearing as "Mr Shithole" in posts on its platform when translated into English from Burmese, apologizing for any offense caused.



Dangerous Catastrophic Failures





يصبحهم = Good morning

לפגוע בהם ~ Attack them

https://www.haaretz.com/israel-news/palestinian-arrested-over-mistranslated-good-morning-facebook-post-1.5459427

Dangerous Catastrophic Failures

HAARETZ | Israel News | All sections | Israel - BDS | Israel settlements | Italy - anti-Semitism | Flake - T

Home > Israel News

Israel Arrests Palestinian Because Facebook Translated 'Good Morning' to 'Attack Them'

No Arabic-speaking police officer read the post before arresting the man, who works at a construction site in a West Bank settlement

Yotam Berger | Oct 22, 2017 1:36 PM

https://www.haaretz.com/israel-news/palestinian-arrested-over-mistranslated-good-morning-facebook-post-1.5459427

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When are (N)MT Errors Dangerous?

- Output is believable (in context)
- Lack of means and/or motivation to verify
- Use case involves MT informing action

Believable Output

Believability = Fluency + Plausibility + Human Judgment

- Fluency: Does it "feel" like the target language?
  - Users more likely to trust fluent output (Martindale & Carpuat 2018)
  - NMT more likely to produce fluent but not adequate output (Martindale et al 2019)
- Plausibility: Does it make sense?
  - MT output is more believable when it is plausible (Work in progress)
- Human: People use heuristics to judge credibility of information[1]

[1] Rieh, S. Y. (2010). "Credibility and cognitive authority of information." In M. Bates & M. N. Maack (Eds.), *Encyclopedia of Library and Information Sciences* (3rd ed., pp. 1337-1344).

When are NMT Errors Dangerous?

- ✓ Output is believable (in context)
- Lack of means and/or motivation to verify
- Use case involves MT informing action

Gist MT?

Proceedings of the 14th Conference of the Association for Machine Translation in the Americas
October 6 - 9, 2020, Workshop on the Impact of Machine Translation

When are Gist MT Errors Dangerous?

Lack of means and/or motivation to verify?

Gist MT use characteristics

- High volume of foreign language text and/or tasks
- Impractical to translate everything or hire only bilinguals
  - Especially bilinguals with domain expertise
- Monolingual domain experts use MT to triage text or glean information
- Ideally: Bilinguals translate/evaluate documents/info monolinguals find
  - In practice: people may cut corners…

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When are Gist MT Errors Dangerous?

Use case involves MT informing action?

Gist MT use examples

- Journalist looking for relevant, local Tweets after an event
- Business analyst monitoring press for info about foreign competitors
- Investigator checking social media as part of background check

Example: USCIS Refugee Vetting

ProPublica Illinois Texas Local Reporting Network Electionland Data Store

PROPUBLICA Graphics & Data Newsletters About

Racial Justice Health Care Politics Environment More...

Google Says Google Translate Can't Replace Human Translators. Immigration Officials Have Used It to Vet Refugees.

Documents shared with ProPublica show that immigration officials have been told to vet refugees' social media posts using Google Translate. Language experts caution even students against using the service.

by Yeganeh Torbati, Sept. 26, 2019, 11:37 a.m. EDT

Appendix C: Translations

Internet Translation Services

The most efficient approach to translate foreign language contents is to utilize one of the many free online language translation services provided by Google, Yahoo, Bing, and other search engines. [redacted] if needed. Use the following steps to translate using Google:

In-Person Translation Services

Occasionally, officers will encounter foreign text written in a dialect or colloquial usage that does not necessarily translate easily using the available online tools mentioned above. Furthermore, there are currently no tools available to translate text written on images. Officers are responsible for determining

"Information collected from social media, by itself, will not be a basis to deny refugee resettlement"

Official statement, September 2019

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Example: USCIS Refugee Vetting

"Information collected from social media, by itself, will not be a basis to deny refugee resettlement" --Official statement, September 2019

However…

- Incorrect MT could tip scales of suspicion (in either direction)
- Social media is out of domain from MT training
- Often low-resource languages

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Is NMT for Gisting Worth the Risk?

- IMHO: Yes!

Good news:

- Truly misleading output is rare
- Faster to read, easier to understand
- Users like it

Just need to mitigate risk

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How can we mitigate the dangers?

Dangers

- Output has errors
- Output is believable (in context)
- Lack of means and/or motivation to verify
- Use case involves MT informing action

Mitigation goals

- ~~Error-free MT~~
- Encourage *appropriate* skepticism
- Make it easier to recognize potential errors
- Verify before acting

How can we mitigate the dangers?

Dangers

- Output has errors
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-Policy interventions
-Technological Interventions

Mitigation Strategies

Policy interventions

- Normative principles organizations with gist MT use cases should follow
- Changes to procedures and training

Technological interventions

- Changes to the technology environment or the technology itself
- Requires additional research and development

Policy Interventions

1. Independent, in-domain evaluation
2. Training for MT users
3. Workflows that require validation before action

P1: Independent, In-Domain Evaluation

Principle: An organization should not deploy or encourage the use of MT without independent evaluation in the domain(s) and language pair(s) it is intended to be used on.

- If the intended use shifts/expands, additional testing should be conducted

Why? MT quality varies by language/domain

Independent – Not conducted by the MT company

Domain – Style and/or topic

Evaluation – Formal or informal

- Evaluators should know source language

P2: Training for MT Users

Principle: Users should be trained to understand the technology well enough to expect variations in quality including dropped or hallucinated words and phrases.

Why? NMT is not intuitive! Hard to recognize what you don't expect.

Example hands-on exercises:

- Change context window, capitalization, punctuation, etc and observe output changes
- Compare output from high- and low- resource languages
- Try to get the system to hallucinate (e.g. fake Hawaiian)

P3: Require Validation Before Action

Principle: Organizations with workflows that include critical decisions or actions informed by MT should require validation by someone who knows the source language before taking action.

Why? Establishing a consistent process deters corner-cutting.

- Even professional translation services rely on at least one level of quality control!

Considerations

- Level of validation proportionate to impact of action/decision
- E.g., Self-validation through other resources *may* be sufficient for minimal-impact actions/decision

Technological Interventions

1. Provide access to multiple MT outputs
2. Provide access to additional language resources
3. Build in “nudges” to help the user recognize quality issues

T1: Multiple MT Outputs

What: Display outputs from two or more MT systems/models

LOE: Moderate

- Obtain licenses and/or build models
- Modify/create interface to display

Why? Users can observe differences to flag possible errors

Anecdote: Users actually prefer this anyway!

T2: Additional Language Resources

What: Provide CAT-like tools to MT users

LOE: Low-Moderate

- Teach users features in existing services (e.g. Google Translate, Systran, Wiktionary, Linguee)
- Obtain access to resources (dictionaries/terminologies/TMs, etc)
- Integrate access alongside MT

Why?

- Individual word lookup can validate/clarify MT output
- Terminologies can resolve technical terms
- TM lookup can provide alternate contexts

T3: Nudges

What: Automatically flag questionable output

- Quality estimation
- Diff on multiple outputs

LOE: High

- QE is an open research area

Why? Draw user's attention to problem areas

Summary

Dangers	**Mitigation goals**	**Recommended Interventions**
• Output has errors	• ~~Error-free MT~~	• *(Continue improving)*
• Output is believable (in context)	• Encourage *appropriate* skepticism	• P1 (Evaluation), P2 (Training), T3 (Nudges)
• Lack of means and/or motivation to verify	• Make it easier to recognize potential errors	• T1 (Multi-outputs), T2 (Lang resources), T3 (Nudges)
• Use case involves MT informing action	• Verify before acting	• P3 (Verify)

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Conclusion

- There can be risks to gist MT use
- Steps can be taken to mitigate them
- These are just examples
- Stakeholders should be looking at these mitigations and others
  - Organizational leadership
  - MT integrators
  - MT researchers
- See also: AI Ethics

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For further information or questions contact:
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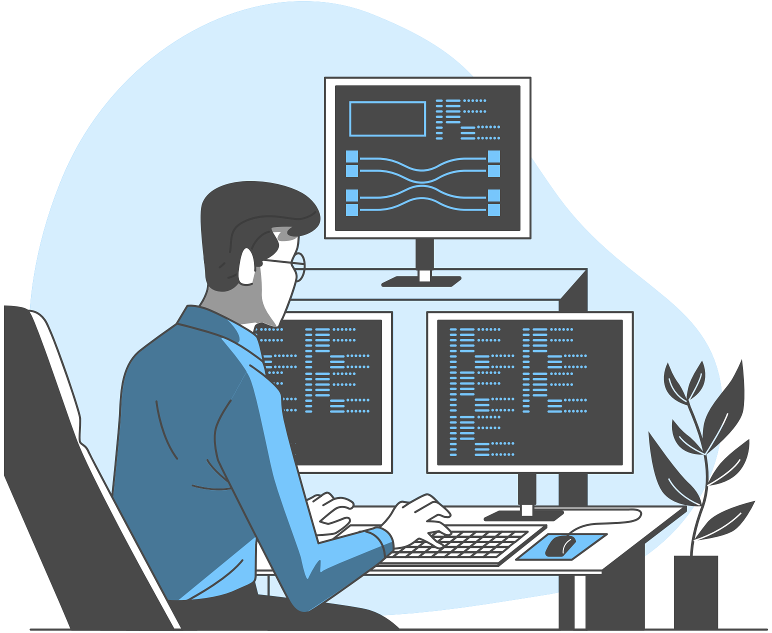


A Different, Ethical MT is Possible:

English-Catalan Free/ Open-Source NMT

Vicent Briva-Iglesias
SFI Centre for Research Training in Digitally-Enhanced Reality (D-REAL), Dublin City University

Overview

01 **Understanding the Problem**
Current context of MT.

02 **Variables**
MT engines and methodology.

03 **Results**
Relative ranking, quality, and post-editing evaluation.

04 **iMpacT**
Effects and use-cases.

Understanding the Problem

01 Catalan context

Minoritized, stateless language. Low-resource.

02 NMT Requirements

Huge computational power (GPUs). Difficulty to find high-quality corpora for low-resource languages.

03 Literacy

You have the corpora. Now, how is an MT engine trained?

04 Data Privacy

Confidential information may be at stake.

What is the iMpacT of open-source MT for low-resource languages?

1. Which MT engine evaluated [Apertium, Softcatalà, Google] offers a higher translation quality?

2. Which MT engine evaluated offers a bigger productivity increase when introducing it into a translation workflow?

3. Can a free/open-source MT engine for a low-resource language beat the flagship MT engine for the English-Catalan language combination?

Variables – MT Engines

Apertium

- Free/Open-Source RBMT engine
- Originally developed for close languages (e.g. ES-CA)

Softcatalà Translator

- Free/Open-Source EN<>CA NMT engine (OpenNMT)
- Trained with TMs from the Softcatalà project («in-domain»)

Google Translate

- Flagship of commercial MT
- NMT from 2020
- Thousands of language combinations (including CA)

Variables – Text

HomeAssistant.io

- Open-source smart home software (GitHub)
- Preparation of the text with Okapi Framework
- Segments chosen randomly for the creation of the samples to be evaluated

Methodology – Human Evaluation 1

Relative Ranking
11 professional evaluators.
200 segments.

Rànquing de TA (Rank Comparison)

Source (English (United Kingdom))

Start	
Current	**This entity does not have a unique ID, therefore its settings cannot be managed from the UI.**
Next	The {platform} integration is not loaded.

Target (Catalan)

0 Aquesta entitat no té un ID únic, per tant la seva configuració no es pot gestionar des de la IU.

0 Aquesta entitat no té un ID únic, per tant, la seva configuració no es pot gestionar des de la interfície d'interès.

0 Aquesta entitat no té un únic ID, per tant no es poden abastar els seus paràmetres des del UI.

(Info)

Comments

Characters left: 500

Methodology – Human Evaluation 2

Adequacy & Fluency

11 professional evaluators.

100 segments.

Precisió i fluïdesa S2, TA2

Source (English (United Kingdom))

Start	
Current	**This service is run by our partner, a company founded by the founders of Home Assistant and Hass.io.**
Next	Go to the integrations page.

Target (Catalan)

Start	
Current	**Aquest servei el gestiona el nostre soci, una empresa fundada pels fundadors de Home Assistant i Hass.io.**
Next	Vés a la pàgina d'integracions.

Fluency:

○ Incomprehensible ○ Disfluent ○ Good ○ Flawless (More Info)

Adequacy:

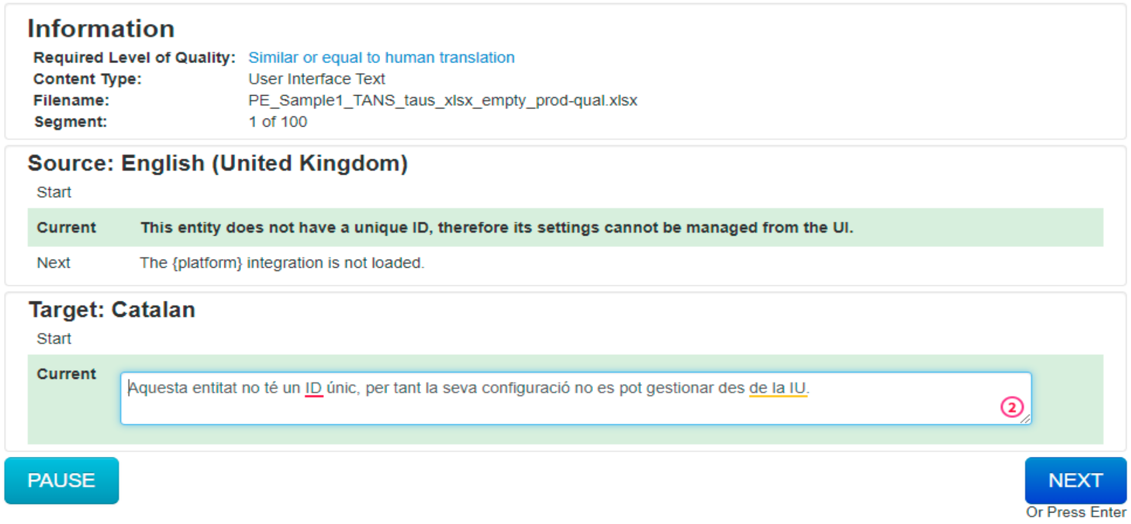
○ None ○ Little ○ Most ○ Everything (More Info)

Methodology – Human Evaluation 3

Post-Editing Evaluation

6 evaluators (2 groups of study: professionals & volunteers).

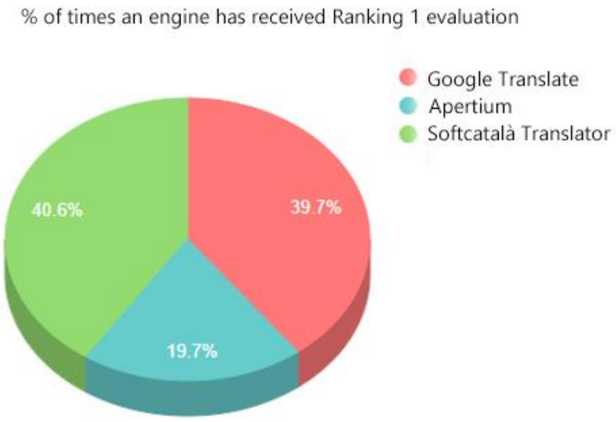
2 texts of 100 segments.

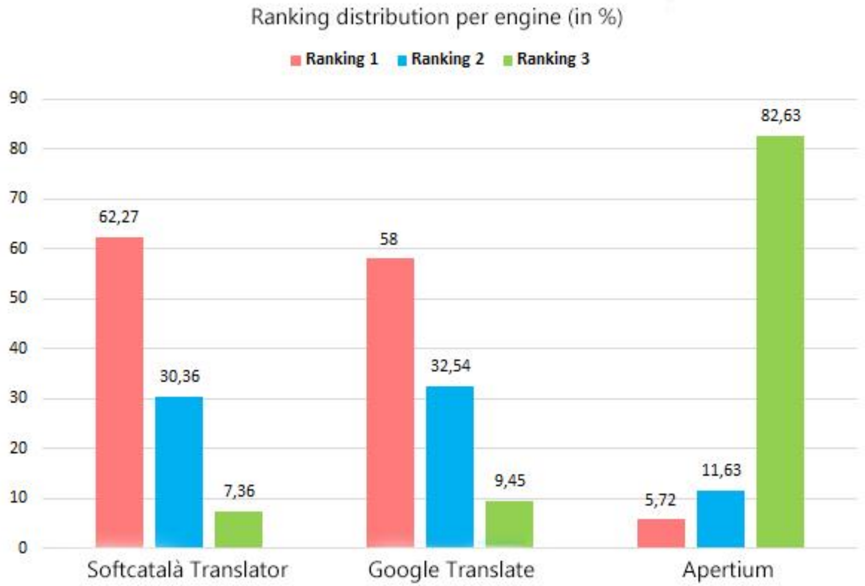


Post-Editing Evaluation (Explanation)

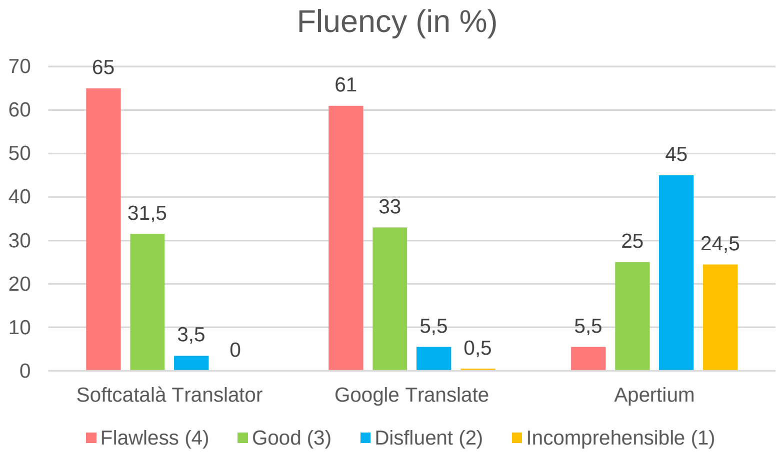
	Text 1, Engine 1	Text 1, Engine 2	Text 2, Engine 1	Text 2, Engine 2
Evaluator 1	✓	✗	✗	✓
Evaluator 2	✗	✓	✓	✗
Evaluator 3	✓	✗	✗	✓
Evaluator 4	✗	✓	✓	✗

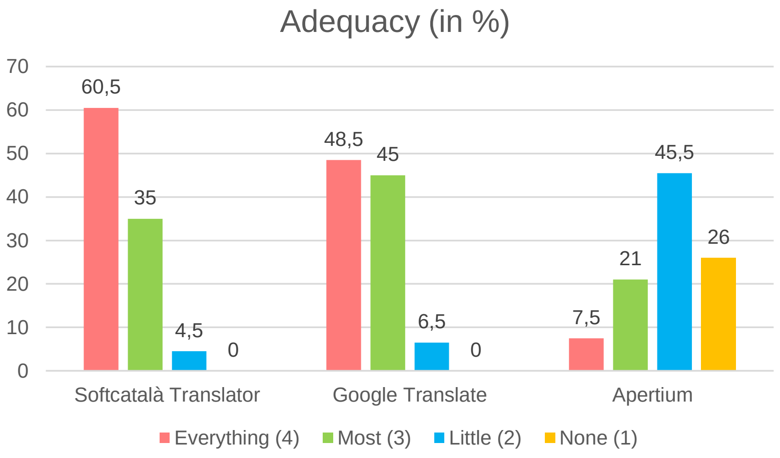
Results – MT Ranking





Results – Fluency & Adequacy





Results – Post-Editing Productivity (group of study 1: Softcatalà-Google)

	Softcatalà Translator	Google Translate
	Median	Median
PE Time (s)	3909.07	4131.64
Edit Distance* (segment)	9.79	10.35

222.563 seconds of difference; 5.69% productivity increase

		1-5 words	6-15 words	16 or >16 words
		Median	Median	Median
PE Time (s)	Softcatalà	8.15	18.44	34.08
	Google	9.41	20.08	33.67
Edit distance* (seg.)	Softcatalà	5.34	11.53	9.79
	Google	12.22	9.31	11.20

Results – Post-Editing Productivity (group of study 2: Softcatalà-Apertium)

	Softcatalà Translator	Apertium
	Median	Median
PE Time* (s)	1859.51	3743.41
Edit Distance* (segment)	6.81	24.85

1883.89 seconds of difference; 101.31 % productivity increase

		1-5 words	6-15 words	16 or >16 words
		Median	Median	Median
PE Time* (s)	Softcatalà	5.95	14.18	25.83
	Apertium	14.11	28.64	55.70
Edit distance* (seg.)	Softcatalà	6.21	10.73	10.11
	Apertium	40.65	37.76	36.15

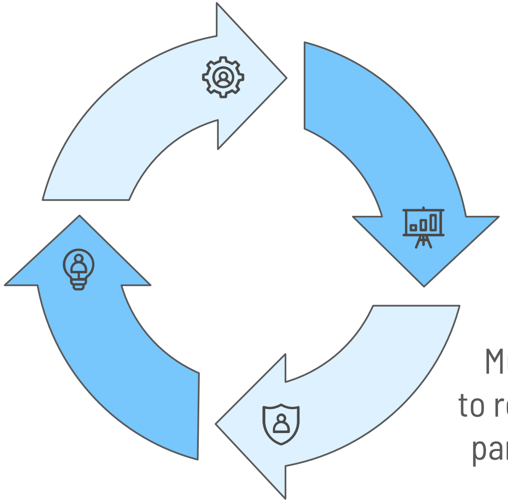
iMpacT and Effects

Normalisation

Low-resource languages gain presence on the Internet, society, etc.

Data Privacy

Confidential information is preserved.



Language Diversity

Avoid language shifts to predominant languages. And fosters language literacy.

Crisis Scenarios

Multilingual communication to reach everyone, e.g. COVID pandemic, natural disasters.

Thanks!

Do you have any questions?

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Gender bias in Neural Machine Translation

Argentina Anna Rescigno
Eva Vanmassenhove
Johanna Monti
Andy Way

6th October 2020

This work has been supported by the Dublin City University Faculty of Engineering & Computing and the University of Naples "L'Orientale" Department of Literary, Linguistic and Comparative Studies under the Erasmus+ Traineeship project number 2019-1-IT02-KA103-061753

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Presentation Outline

www.adaptcentre.ie

- **Introduction**
  - A Note on Terminology
  - A Quick Problem Sketch
- **Experimental setup**
  - Compilation of Datasets
  - Description of the MT systems
- **Results & Analysis**
- **Three main points:**
  - Why does this kind of bias matter
  - What is its impact and on whom
  - Why we need to correct this bias
- **Conclusions and Future Work**

Introduction

3

Introduction: a note on terminology

www.adaptcentre.ie

Natural Gender
*"Gender based on the **sex** or, for neuter, the lack of sex of the referent of a noun, as English girl (<u>feminine</u>) is referred to by the feminine pronoun she, boy (<u>masculine</u>) by the masculine pronoun he, and table (neuter) by the <u>neuter</u> pronoun it."*
Collins Dictionary 2018, HarperCollins, London, viewed September 2020 http://www.collinsdictionary.com

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Introduction: a note on terminology

Natural Gender	Grammatical Gender
*"Gender based on the **sex** or, for neuter, the lack of sex of the referent of a noun, as English girl (feminine) is referred to by the feminine pronoun she, boy (masculine) by the masculine pronoun he, and table (neuter) by the neuter pronoun it."*	*"Gender based on arbitrary assignment, without regard to the referent of a noun, as in French 'le livre' (masculine), "the book," and German 'das Mädchen' (neuter), "the girl."*
Collins Dictionary 2018, HarperCollins, London, viewed September 2020 http://www.collinsdictionary.com	*Collins Dictionary* 2018, HarperCollins, London, viewed September 2020 http://www.collinsdictionary.com

Introduction: a note on terminology

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Natural Gender	Grammatical Gender	Social Gender
*“Gender based on the **sex** or, for neuter, the lack of sex of the referent of a noun, as English girl (<u>feminine</u>) is referred to by the feminine pronoun she, boy (<u>masculine</u>) by the masculine pronoun he, and table (neuter) by the <u>neuter</u> pronoun it.”* *Collins Dictionary* 2018, HarperCollins, London, viewed September 2020 http://www.collinsdictionary.com	*“Gender based on arbitrary assignment, without regard to the referent of a noun, as in French ‘le livre’ (masculine), “the book,” and German ‘das Mädchen’ (neuter), “the girl.”* *Collins Dictionary* 2018, HarperCollins, London, viewed September 2020 http://www.collinsdictionary.com	- *Embedded in the lexicon of many languages* - *Systematic structural bias.* - *Masculine forms the default for generic use.*

6

Introduction: a note on terminology

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Romance Languages (e.g. ES, FR, IT)

- animate/persons/animals

↓

grammatical gender = natural gender

- inanimate objects

↓

grammatical gender = arbitrary

Introduction: a note on terminology

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Romance Languages (e.g. ES, FR, IT)	English
• animate/persons/animals ↓ grammatical gender = natural gender • inanimate objects ↓ grammatical gender = arbitrary	• grammatical gender is not inflectional • ***pronominal gender*** → gender expressed through the pronouns = natural gender • ***gender-neutralization*** of the language

8

Introduction: a quick problem sketch

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A simple example:

I am happy!

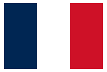
Io sono contento!

Io sono contenta!

[Natural Gender]

[Grammatical Gender]

I am happy!



Je suis heureux!

Je suis heureuse!

[Natural Gender]

[Grammatical Gender]

9

Introduction: a quick problem sketch

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		Subject gender	Predicative nominative gender	Agreement?
English	Mark is an efficient nurse.	M	covered	/
Italian	Mark è un'infermiera efficiente.	M	F	X
French	Mark est une infirmière efficace.	M	F	X
Spanish	Mark es una enfermera eficiente.	M	F	X

Nov 2019

- ➢ **Lack of diversity** → preference for masculine & gender-bias exemptions
- ➢ **Agreement errors**

10

Experimental Setup

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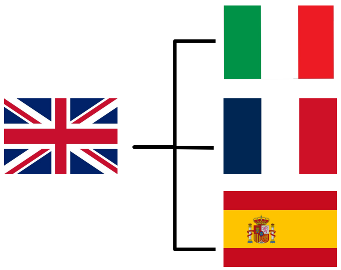
Gender bias in MT

Google Translate

DeepL Translator

Bing Microsoft Translator



- personality adjectives
- profession nouns
- bigender nouns (in Italian)
  - minimal sentence “I am a(n)...”
  - sentence with a referring adjective

	#	Sources
Adjectives	136	(I, 2019a); (II, 2019a);(III, 2019)
Professions	107	(I, 2019b); (II, 2019b)
Bigender	30	(Cacciari et al., 1997); (Cacciari et al., 2011) (Thornton and Anna, 2004)

Table 1: Overview of adjectives, profession and bigender nouns along with the sources from which they were retrieved

Compilation of Datasets

	#	Sources
Adjectives	136	(I, 2019a); (II, 2019a);(III, 2019)
Professions	107	(I, 2019b); (II, 2019b)
Bigender	30	(Cacciari et al., 1997); (Cacciari et al., 2011) (Thornton and Anna, 2004)

Table 1: Overview of adjectives, profession and bigender nouns along with the sources from which they were retrieved

English	**Italian**		**French**		**Spanish**	
I am an assistant.	Sono un assistente.	M	Je suis un assistant.	M	Soy asistente.	*
I am a beautiful assistant.	**Sono una bellissima assistente.**	**F**	**Je suis une belle assistante.**	**F**	**Soy una bella asistente.**	**F**
I am an efficient assistant.	Sono un assistente efficiente.	M	Je suis un assistant efficace.	M	Soy un asistente eficiente.	M

I am a translator.	Sono un traduttore.	M	Je suis un traducteur.	M	Soy un traductor.	M
I am a beautiful translator.	**Sono una bellissima traduttrice.**	**F**	**Je suis une belle traductrice.**	**F**	**Soy una bella traductora.**	**F**
I am an efficient translator.	Sono un traduttore efficiente.	M	Je suis un traducteur efficace.	M	Soy un traductor eficiente.	M

13

Description of MT systems

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Google Translate

- 2003
- statistical MT system
- 2016 → neural MT system
- 2018 → double alternatives on word level

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Description of MT systems

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Google Translate

DeepL Translator

- 2017
- convolutional neural networks
- Linguee database (dictionary)
- nine languages supported
- provides not morphological alternatives
- serves also as glossary

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Description of MT systems

Google Translate

DeepL Translator

Bing Microsoft Translator

- originally a statistical MT system
- switched to a neural system
- does not provides alternatives but
- provides examples of usage

Engaging Content
Engaging People

Results & Analysis

Results & Analysis

❑ ADJECTIVES

ADJ	GT	BMT	DL
F	37.3	1.5	22.8
M	**39.2**	**58.8**	**45.6**
N	20.7	33.1	26.5
Other	2.8	6.5	5.1
Total	100	100	100

Table 2: Results in % for male (M), female (F) and neutral (N) adjectives generated for EN → IT for GT, BMT and DL. The "Other" label includes all results obtained that do not correspond to the "adjective" category

Results & Analysis

- NOUNS

NOUN	GT	BMT	DL
F	35.8	0.9	7.5
M	**46.1**	**60.4**	**60.4**
N	17.6	28.3	28.3
Other	0.6	10.5	3.7
Total	100	100	100

Table 3: Results in % for male (M), female (F) and neutral (N) nouns generated for EN $\rightarrow$ IT for GT, BMT and DL. The "Other" label includes all results obtained that do not correspond to the "noun" category

Results & Analysis

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BMT	IT			FR			ES		
	F	M	N	F	M	N	F	M	N
no adj.	10.0	**86.7**	Q^*	10.0	**63.3**	26.7	3.3	**66.7**	30.0
beautiful	**63.3**	36.7	0.0	43.3	**56.7**	0.0	**66.7**	33.3	0.0
other adj.	13.3	**83.3**	Q^*	3.3	**96.7**	0.0	6.7	**93.3**	0.0
DL	**IT**			**FR**			**ES**		
	F	M	N	F	M	N	F	M	N
no adj	30.0	**70.0**	0.0	20.0	**63.3**	16.7	3.3	**76.6**	20.0
beautiful	**83.3**	16.7	0.0	**73.3**	26.7	0.0	**96.7**	3.3	0.0
other adj.	**53.3**	43.3	Q^*	13.3	**83.3**	3.3	6.7	**93.3**	0.0
GT	**IT**			**FR**			**ES**		
	F	M	N	F	M	N	F	M	N
no adj.	6.7	**93.3**	0.0	6.7	**90.0**	3.3	3.3	**66.7**	30.0
beautiful	43.3	**56.7**	0.0	**80.**	20.0	0.0	**80.0**	20.0	0.0
other adj.	3.3	**96.7**	0.0	3.3	**96.7**	0.0	3.3	**96.7**	0.0

Table 4: Results in % for male (M), female (F) and neutral (N) forms generated for EN → IT, FR and ES for BMT, DL and GT

- *beautiful*

other adjectives:

- *efficient*
- *intelligent*
- *sad*
- *famous*

Results & Analysis

BMT	IT			FR			ES		
	F	M	N	F	M	N	F	M	N
no adj.	10.0	**86.7**	Q^*	10.0	**63.3**	26.7	3.3	**66.7**	30.0
beautiful	**63.3**	36.7	0.0	43.3	**56.7**	0.0	**66.7**	33.3	0.0
other adj.	13.3	**83.3**	Q^*	3.3	**96.7**	0.0	6.7	**93.3**	0.0
DL	IT			FR			ES		
	F	M	N	F	M	N	F	M	N
no adj	30.0	**70.0**	0.0	20.0	**63.3**	16.7	3.3	**76.6**	20.0
beautiful	**83.3**	16.7	0.0	**73.3**	26.7	0.0	**96.7**	3.3	0.0
other adj.	**53.3**	43.3	Q^*	13.3	**83.3**	3.3	6.7	**93.3**	0.0
GT	IT			FR			ES		
	F	M	N	F	M	N	F	M	N
no adj.	6.7	**93.3**	0.0	6.7	**90.0**	3.3	3.3	**66.7**	30.0
beautiful	43.3	**56.7**	0.0	**80.**	20.0	0.0	**80.0**	20.0	0.0
other adj.	3.3	**96.7**	0.0	3.3	**96.7**	0.0	3.3	**96.7**	0.0

Table 4: Results in % for male (M), female (F) and neutral (N) forms generated for EN $\rightarrow$ IT, FR and ES for BMT, DL and GT

- *beautiful*

other adjectives:

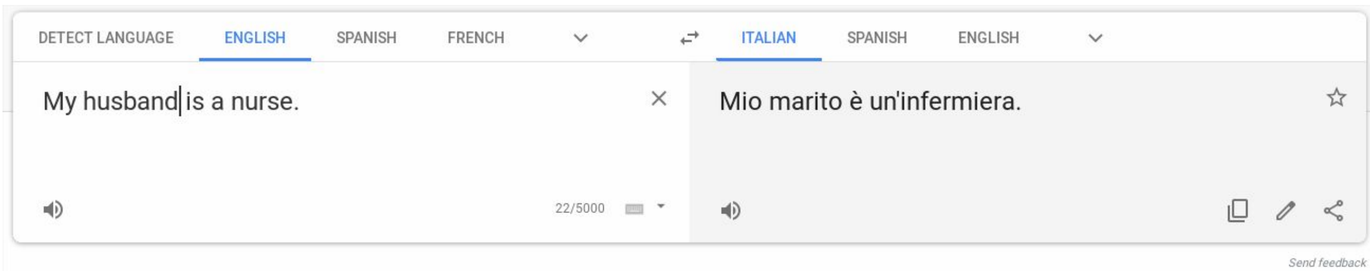
- *efficient*
- *intelligent*
- *sad*
- *famous*

Engaging Content
Engaging People

iMpacT

22

- **From a linguistic point of view:**
  - Avoiding basic gender agreement mistakes



- **From a technological point of view:**
  - Solving these issues is not trivial (see attempts Google)
  - Black box of NLP (we have no/little control over the actual output that are being generated)
- **From a societal/ethical point of view:**
  - Identifying biases in current state-of-the-art systems is important so they don't end up getting mistaken for 'objective' translations
  - if an MT system is being used without human in the loop: real-world consequences

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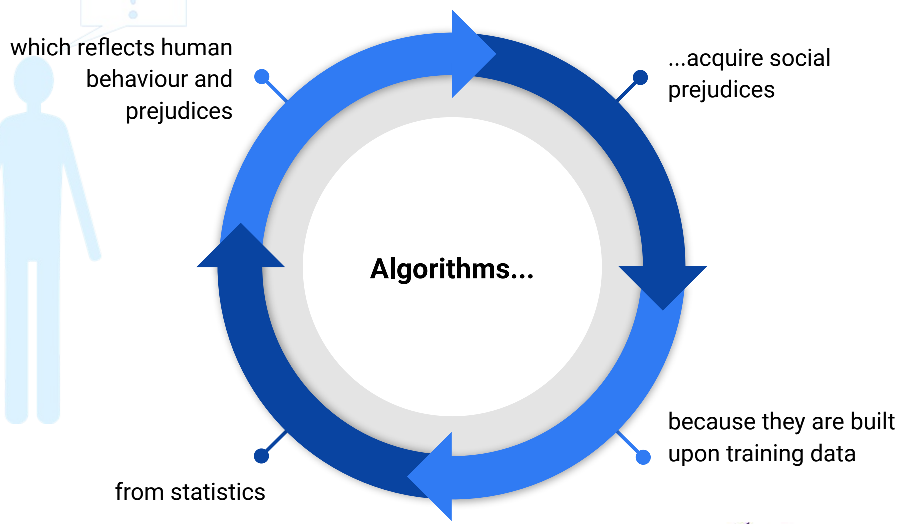
Break the cycle

- ➔ more **bias**
  - ○ ***social***
  - ○ ***gender***
  - ○ ***ethnic***
  - ○ ***...***
- ➔ **exclusion**



Conclusion and Future Work

25

Conclusion and Future Work

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Conclusion:

- Remove gender bias in training data
- Train algorithms to address the problem
- Stop using masculine “neutral” in machine learning texts
- Evaluation of gender phenomena is challenging

Future Work:

- Extend to other language pairs (different languages → different gender phenomena)
- Larger evaluation of more diverse set of words
- Create language specific challenge sets to evaluate how biased is an MT system
- Train our own MT system to verify whether machine bias influences the output of the translation

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Thank you for your attention!

This work has been supported by the Dublin City University Faculty of Engineering & Computing under the Daniel O'Hare Research Scholarship scheme and by the ADAPT Centre for Digital Content Technology, funded under the SFI Research Centres Programme (Grant 13/RC/2106) and co-funded under the European Regional Development Fund, by the European Commission as part of the FALCON project (contract number 610879)

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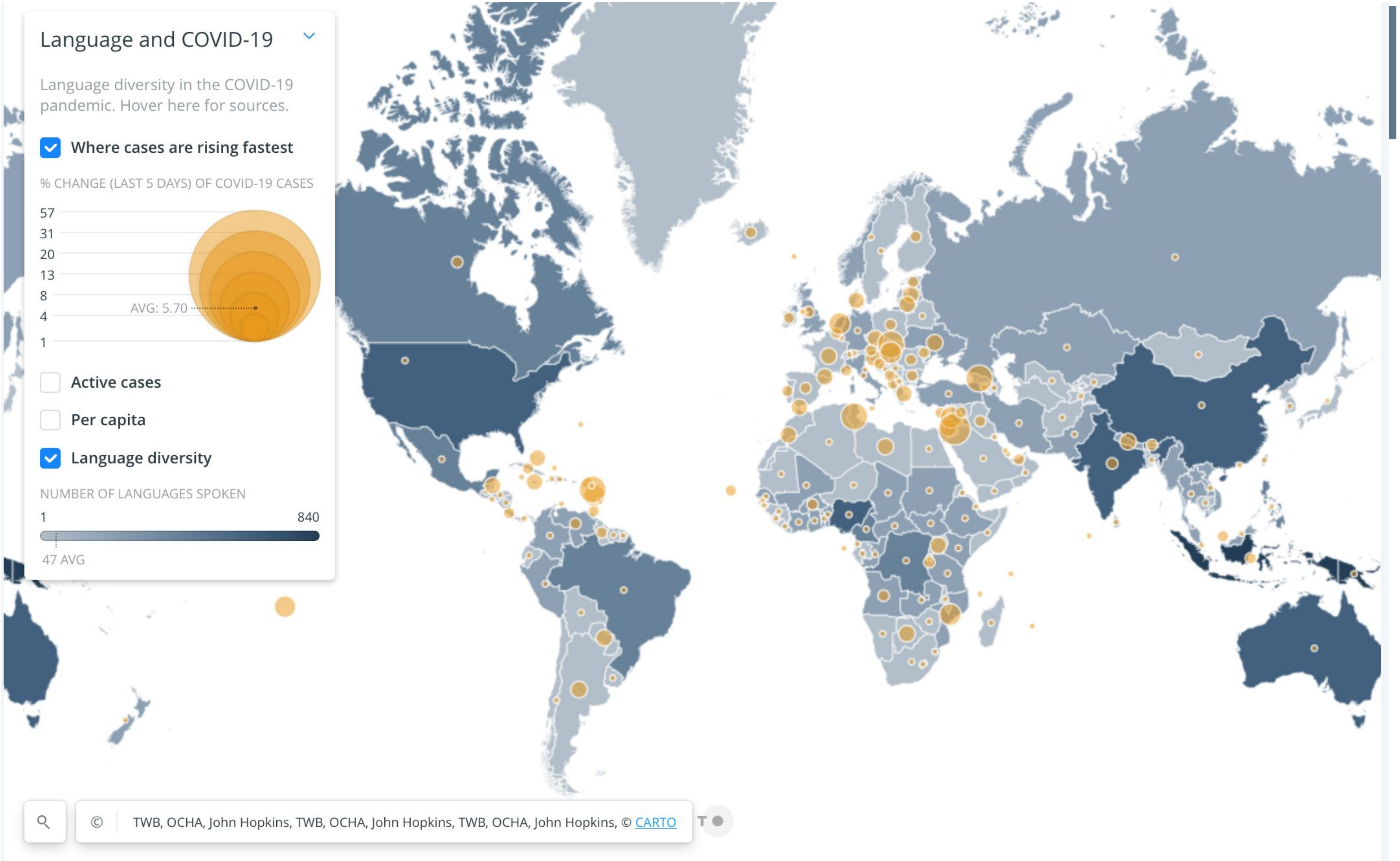
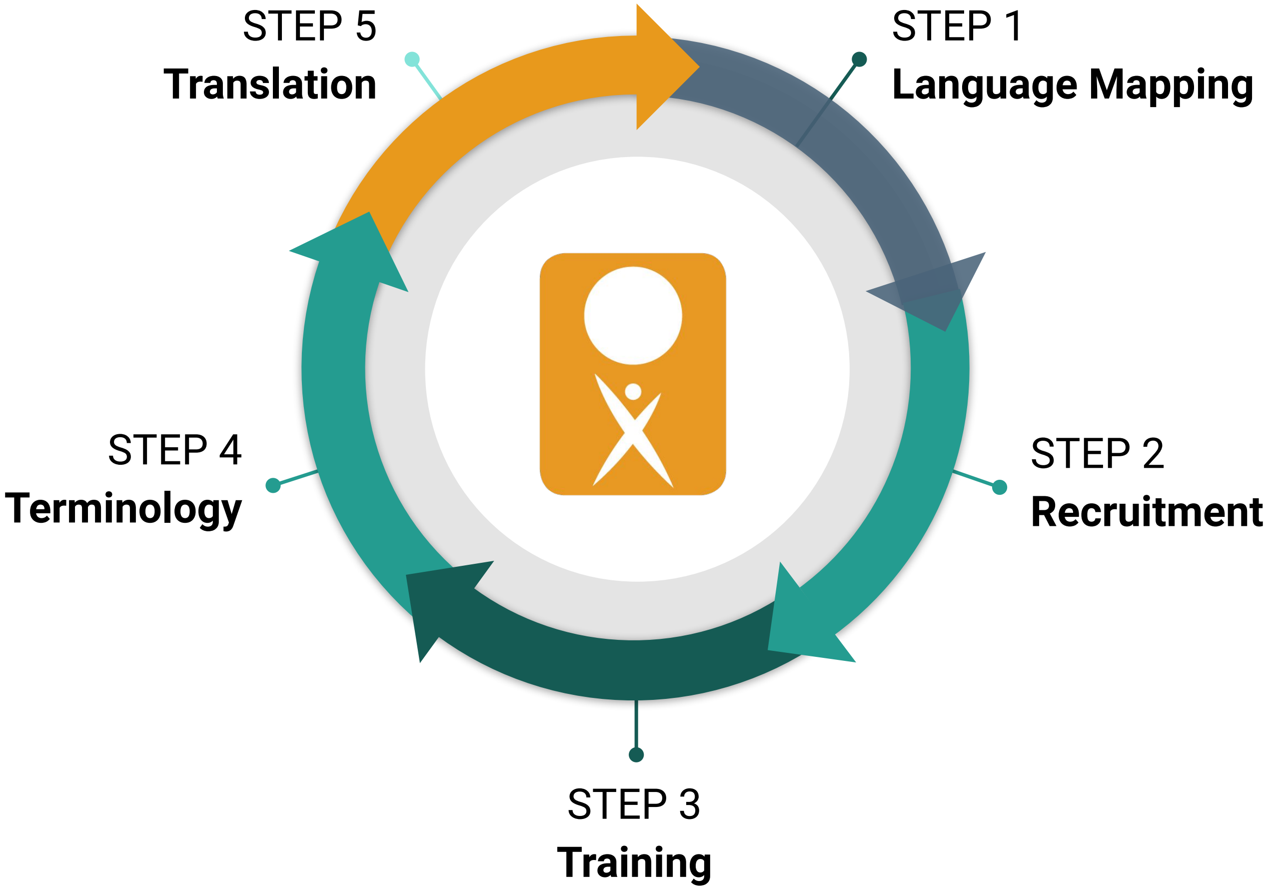
Empowering translators of marginalized languages through the use of language technology

Alp Öktem, Manuel Locria, Eric Paquin, Grace Tang

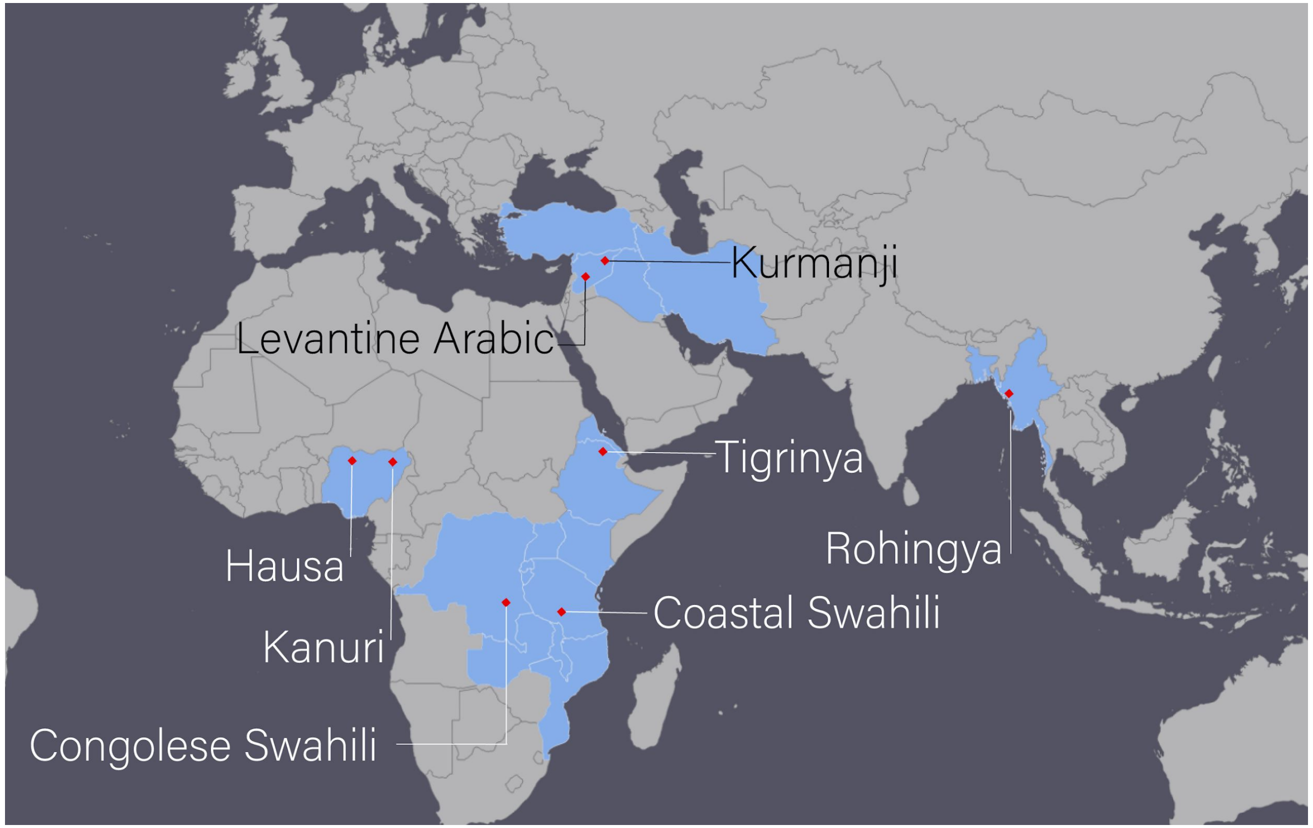
TRANSLATORS WITHOUT BORDERS


Language and COVID-19
Language diversity in the COVID-19 pandemic. Hover here for sources.
Where cases are rising fastest
% CHANGE (LAST 5 DAYS) OF COVID-19 CASES
57
31
20
13
8
4
AVG: 5.70
1
Active cases
Per capita
Language diversity
NUMBER OF LANGUAGES SPOKEN
1
840
47 AVG
©
TWB, OCHA, John Hopkins, TWB, OCHA, John Hopkins, TWB, OCHA, John Hopkins, © CARTO

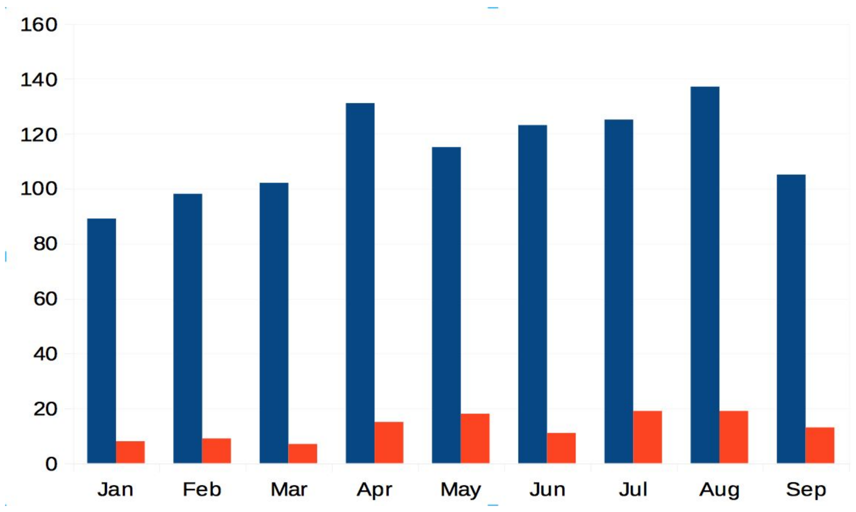
Linguistic crisis response



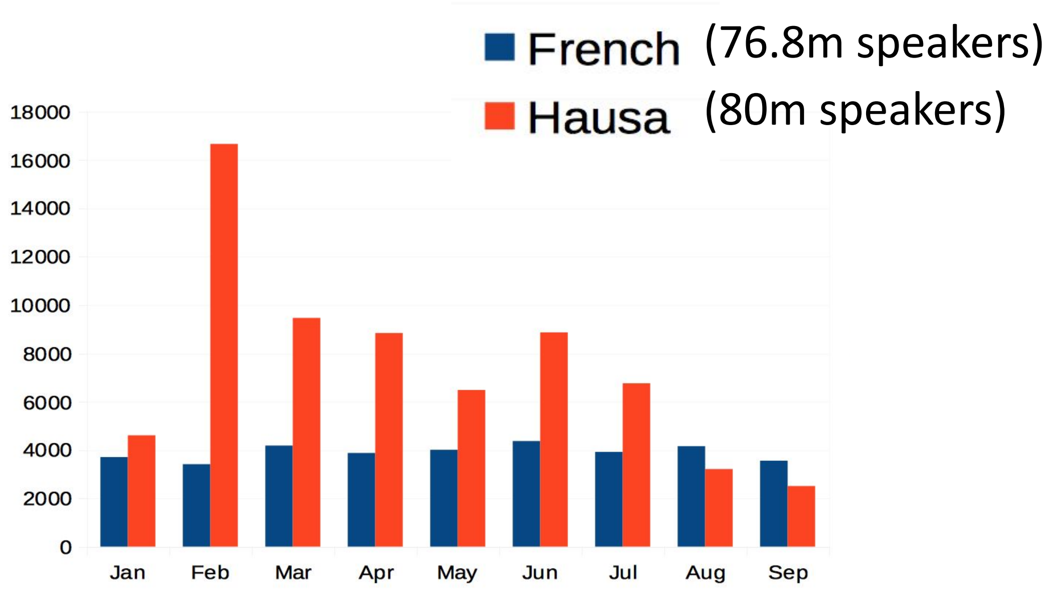
Linguistic crisis response



Hausa vs. French



Volunteer translators

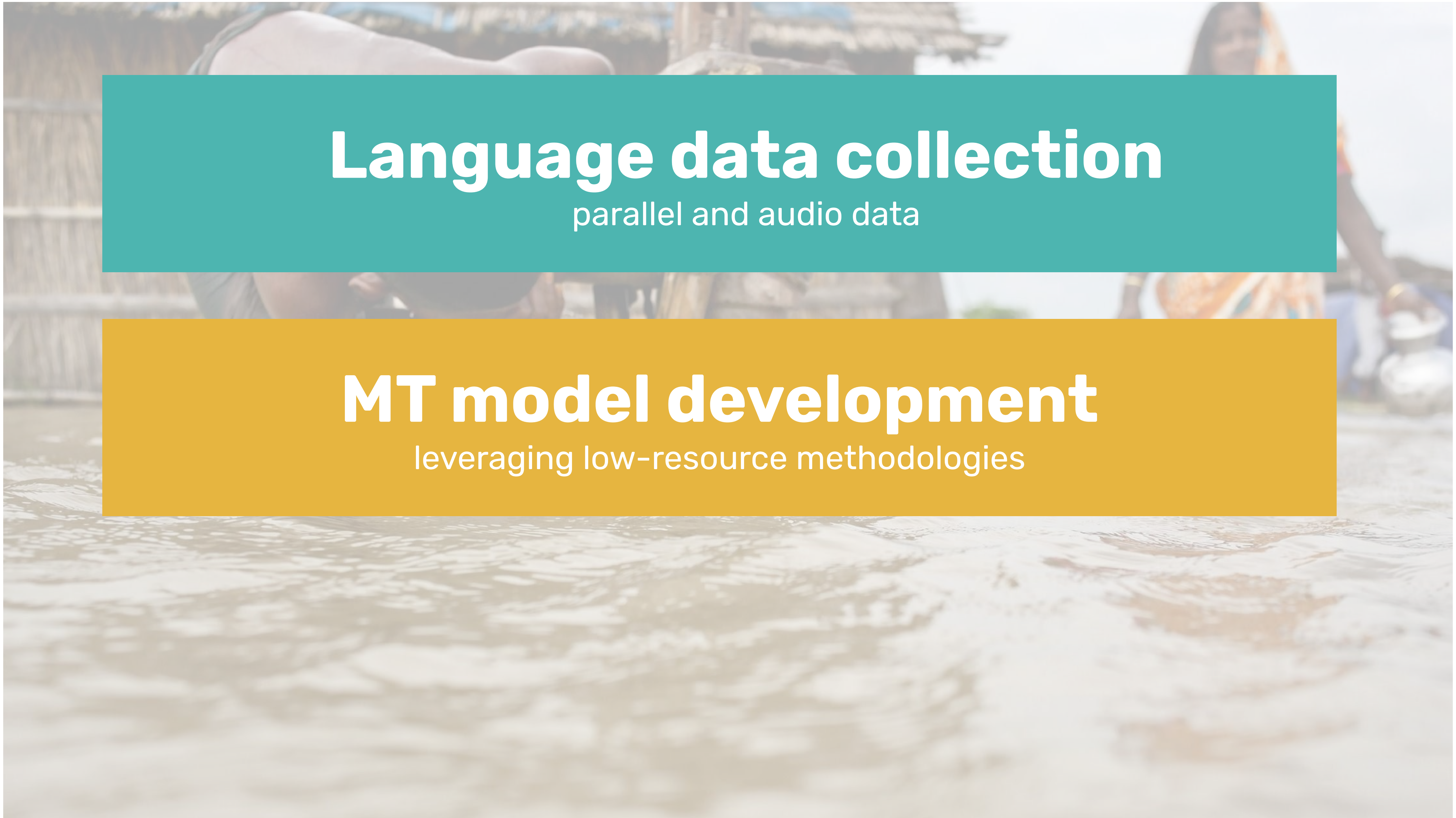


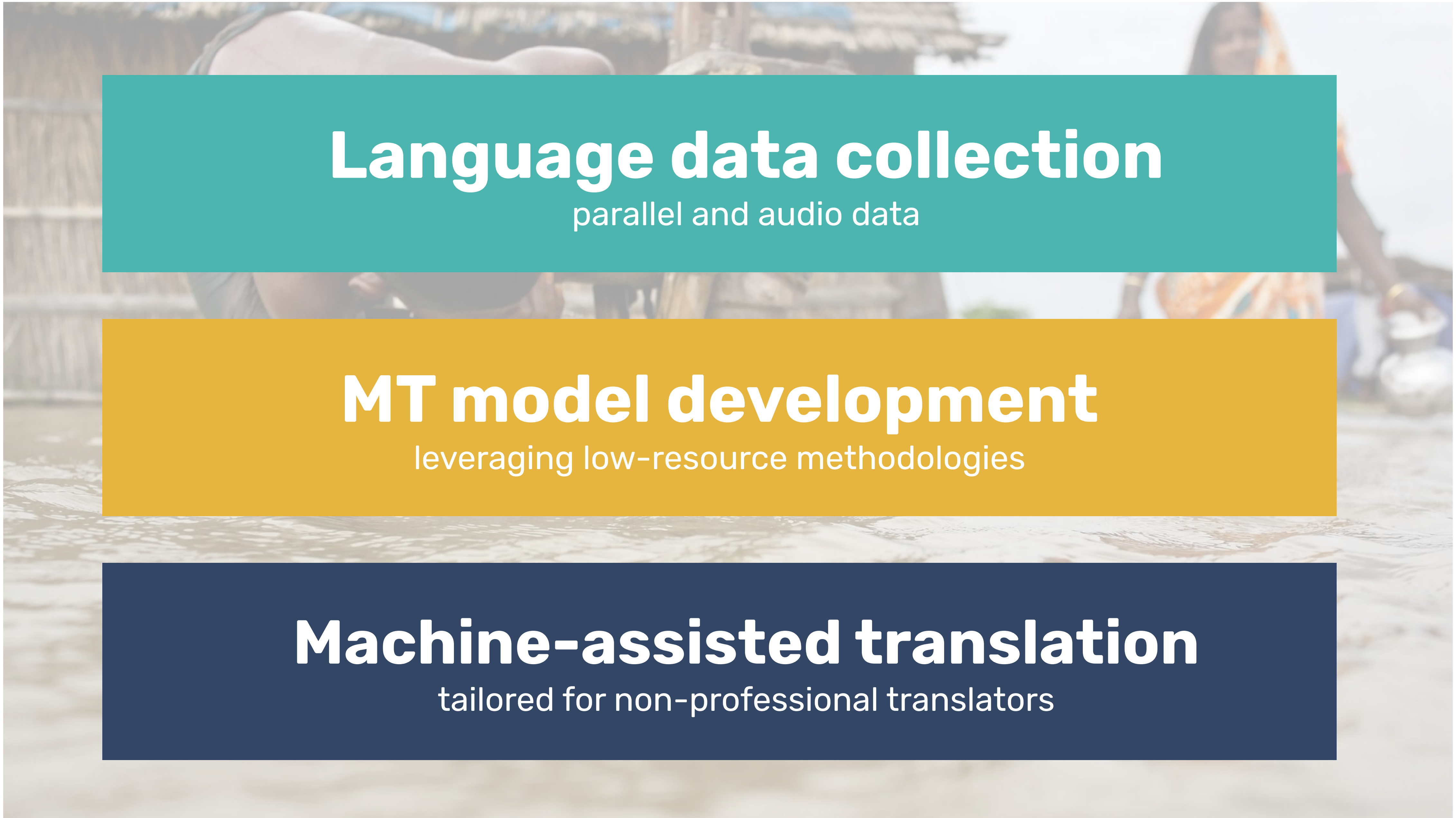
Word count/translator

Data from Kato: TWB's translation platform during Covid-19 pandemic

How can
language technology help
to empower translators of **marginalized languages**?


Language data collection
parallel and audio data


Language data collection
parallel and audio data
MT model development
leveraging low-resource methodologies

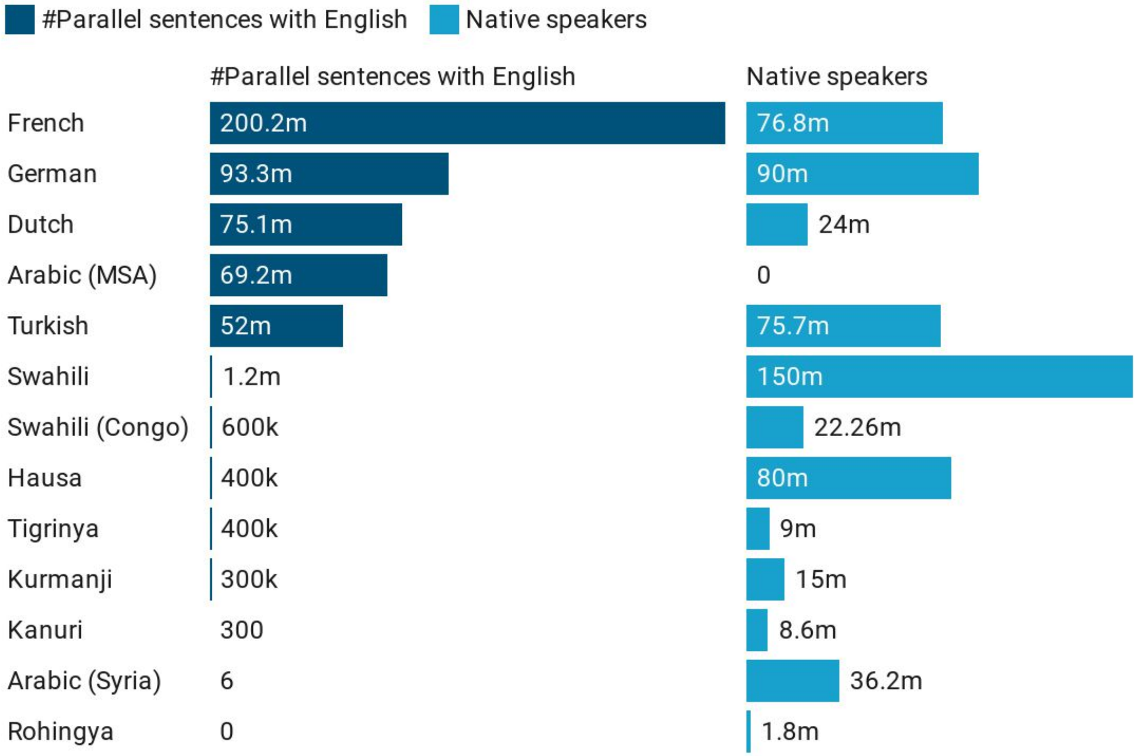

Language data collection
parallel and audio data
MT model development
leveraging low-resource methodologies
Machine-assisted translation
tailored for non-professional translators


Language data collection

NMT for humanitarian impact

Language Data Disparity

Data has been consolidated from the OPUS collection of publicly available parallel corpora paired with English.



Gamayun kits

- Starting point for developing audio and text corpora for languages without pre-existing data resources.
- Four dataset versions:
  - Mini-kit - 5,000 sentences
  - Small-kit - 10,000 sentences
  - Medium-kit - 15,000 sentences
  - Large-kit - 30,000 sentences.
- Source sentences in English, Spanish, French
- Freely available from https://gamayun.translatorswb.org/
  - Currently mini-kits in Hausa, Kanuri, Rohingya, Swahili, Nande

Data | MT | Application

MT model development

MT model development

- Languages: Levantine Arabic, Tigrinya, Congolese Swahili
- Main techniques employed:
  - Domain adaptation
  - Dialect adaptation
  - Cross-lingual transfer learning
  - Back-translation

Data | **MT** | Application

Domain/dialect adaptation

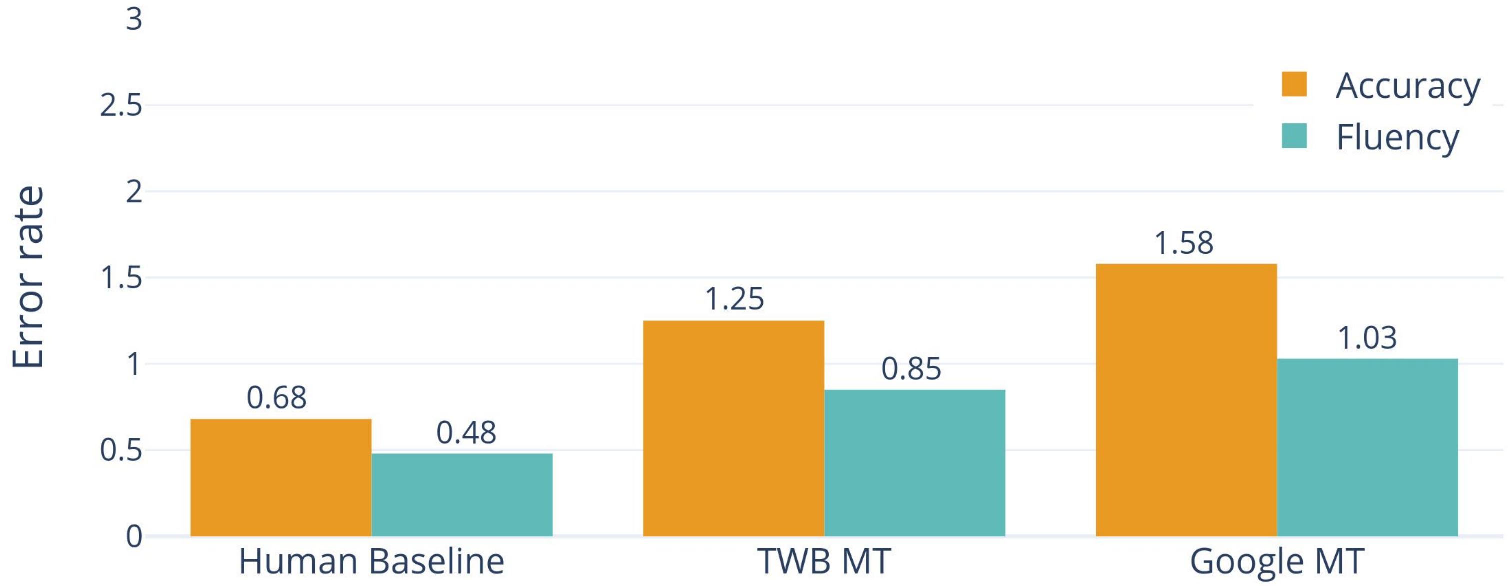
- Levantine Arabic to English machine translation
- For social media content by Syrian refugees in Jordan
- Small in-domain data (5200 sentences)
- Modern Standard Arabic as base model

KHABRONA
خبرونا .INFO

WFP
World Food Programme

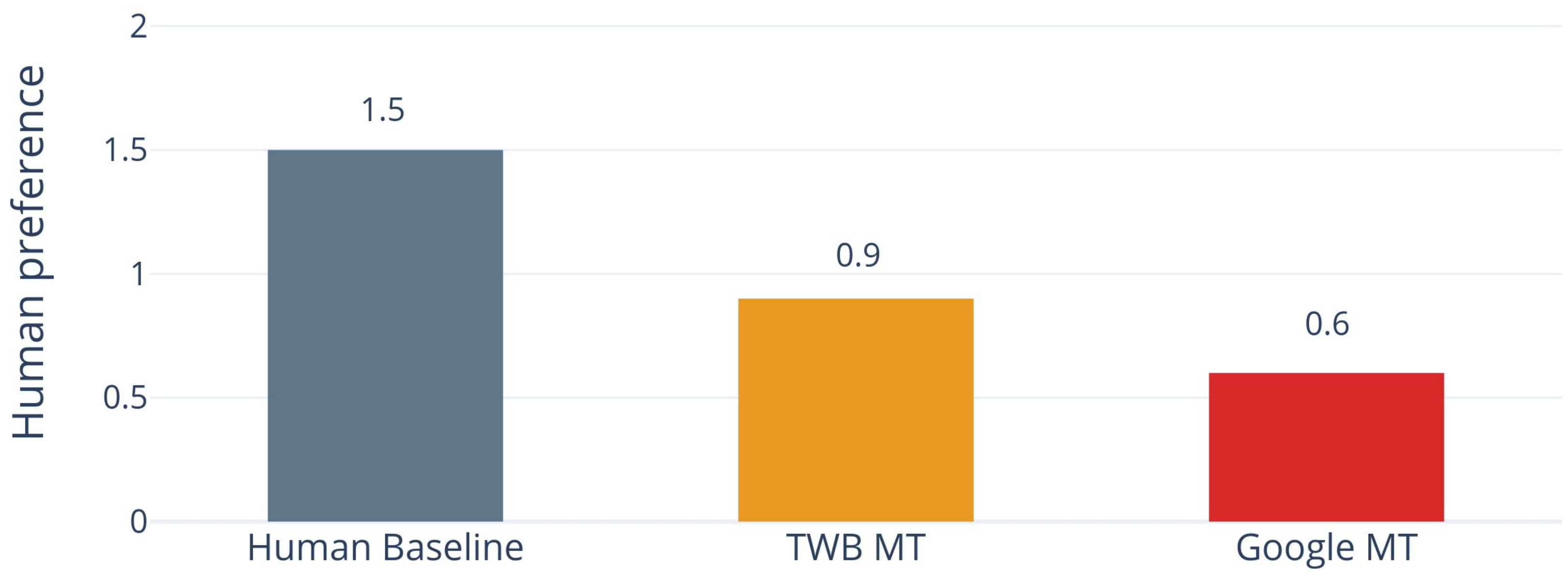
Data | **MT** | Application

Domain/dialect adaptation



Manual evaluation of TWB's Levantine Arabic MT for usability in social media monitoring

Domain/dialect adaptation



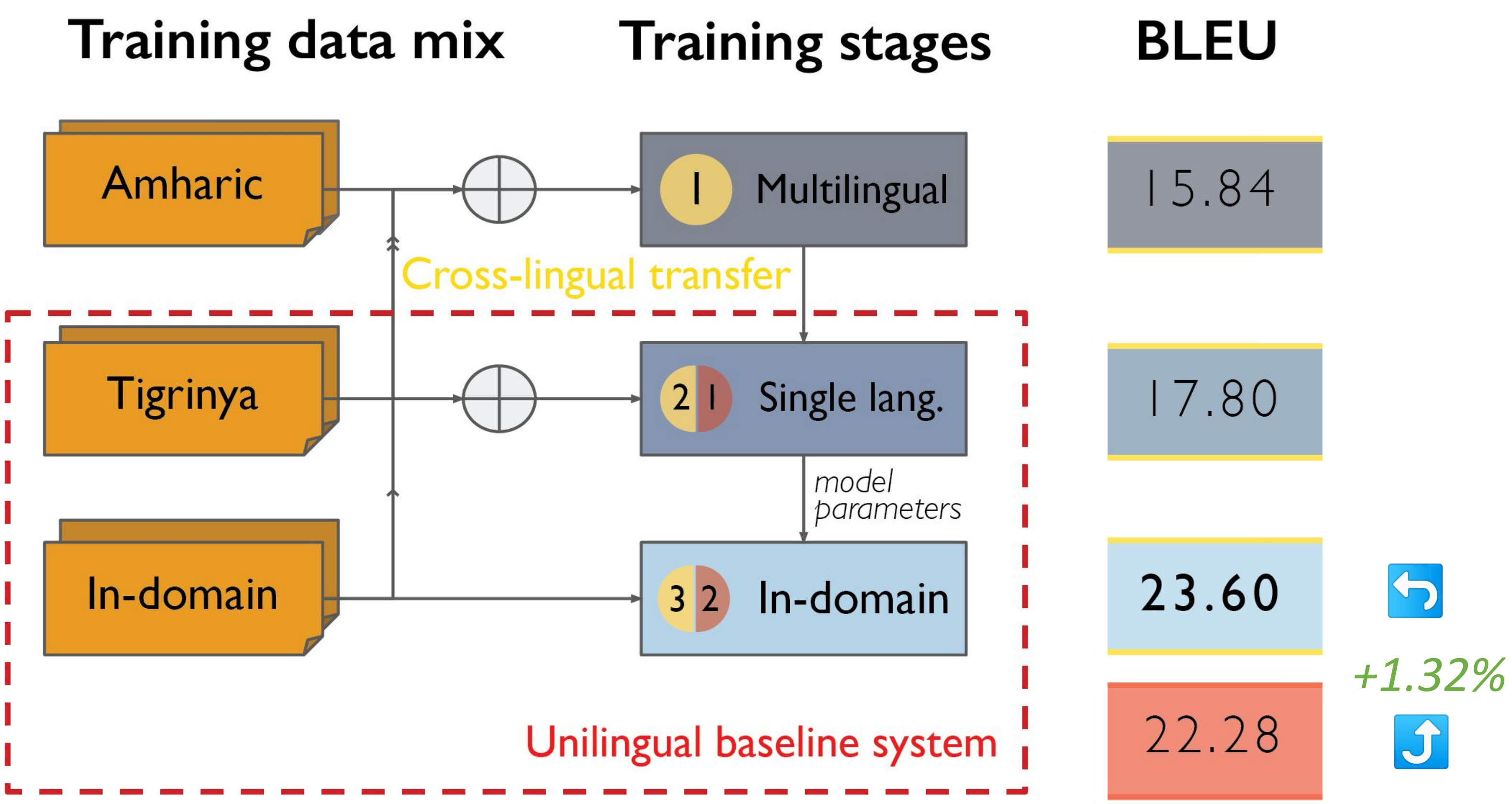
Tigrinya NMT

ትግርኛ

- Semitic language with estimate # speakers of 7.9 million
- Refugee language in Europe and USA
- Hard-to-resource for translation
  - 3 active translators
  - %81 claimed in 2020
  - 72-day average delay
- Transfer learning from Amharic

Data | **MT** | Application

Tigrinya NMT



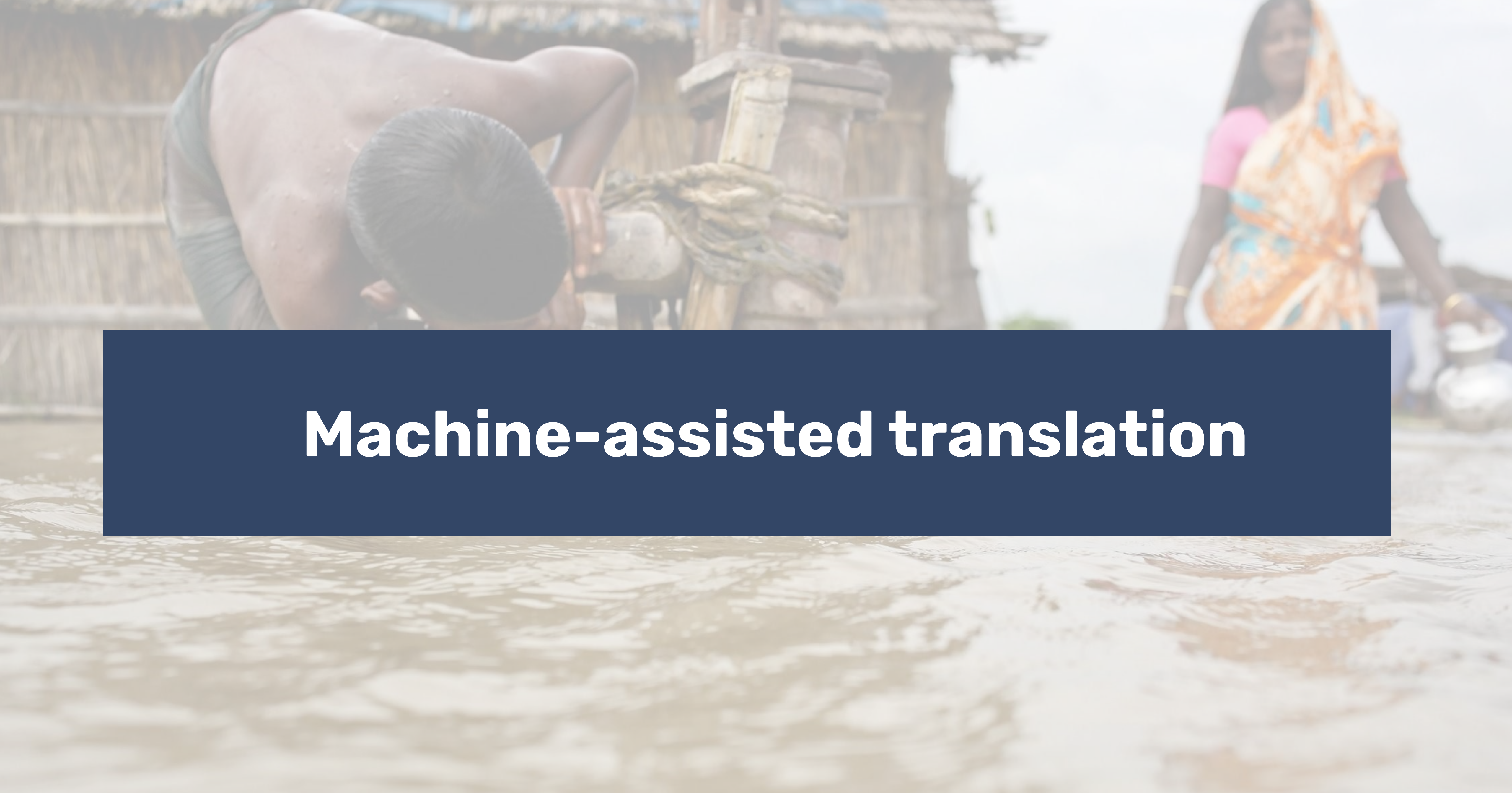
Cross-lingual transfer learning and domain adaptation

Tigrinya NMT

- Bidirectionality challenge:
  - Tigrinya-to-English: 23.60 BLEU
  - English-to-Tigrinya: 9.92 BLEU
- More details on paper:
  - A. Öktem, M. Plitt, G. Tang. *Tigrinya neural machine translation with transfer learning for humanitarian response.* AfricaNLP Workshop organized within ICLR, Addis Ababa, Ethiopia, April 2020.

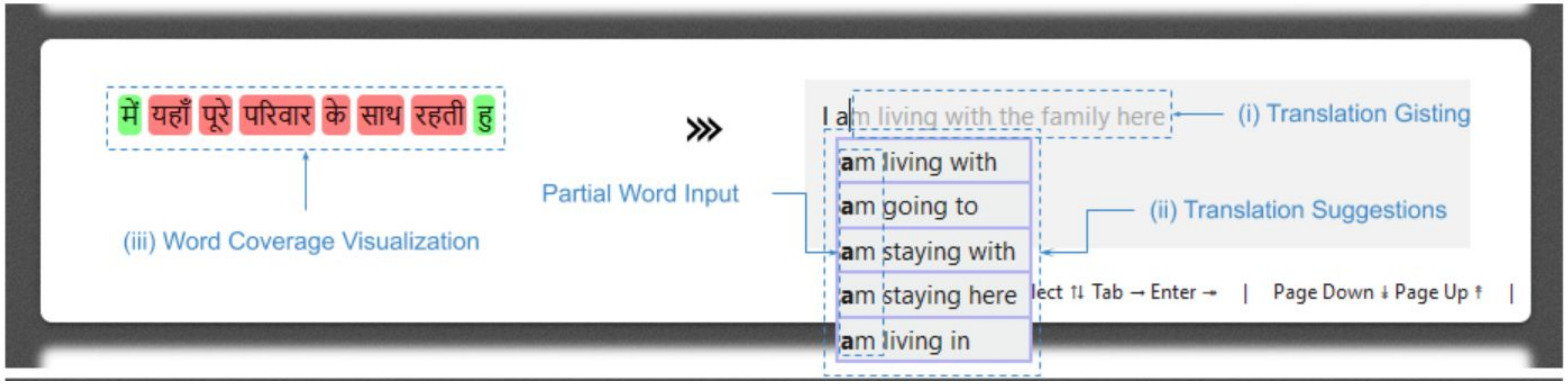
https://gamayun.translatorswb.org/

Data → **MT** → Application


Machine-assisted translation

Interactive Machine Translation

- Proof-of-concept by Microsoft Research India
- Assisted translation through:
  - on-the-fly hints
  - suggestions
- Alternative to post-editing



Santy, Dandapat, Choudhury, Bali. “INMT: Interactive Neural Machine Translation Prediction”. EMNLP 2019

Interactive Machine Translation

- Faster turnaround of document translations
    - compared to manual, and post-edited

Word Coverage and Translation Gisting	Suggestions	Keystrokes
उसी प्रकार मानसिक स्वास्थ्य के लिए ज्ञान की प्राप्ति आवश्यक है Similarly , knowledge for mental health is necessary .	Similarly , In the The knowledge Thus , So the	↓ ↓ Enter ↩
उसी प्रकार मानसिक स्वास्थ्य के लिए ज्ञान की प्राप्ति आवश्यक है **In the** same way , knowledge of knowledge is essential for mental health	same way	Tab Tab Tab Tab
उसी प्रकार मानसिक स्वास्थ्य के लिए ज्ञान की प्राप्ति आवश्यक है **In the same way , knowledge** of knowledge is essential for mental health	of knowledge is essential is necessary for mental	i
उसी प्रकार मानसिक स्वास्थ्य के लिए ज्ञान की प्राप्ति आवश्यक है **In the same way , knowledge i**s essential for mental health	**i**s essential for **i**s necessary for **i**s required to	Enter ↩
उसी प्रकार मानसिक स्वास्थ्य के लिए ज्ञान की प्राप्ति आवश्यक है **In the same way , knowledge is essential for mental health**		Page ↓

Santy, Dandapat, Choudhury, Bali. “INMT: Interactive Neural Machine Translation Prediction”. EMNLP 2019

Interactive Machine Translation

- Faster turnaround of document translations
  - compared to manual, and post-edited
- Human-machine collaboration to best leverage low-resource models

	Data Size	0%	10%	20%	40%
bn-en	1.1M	25.31	27.54	35.68	54.03
hi-en	1.5M	40.64	42.06	47.90	62.18
ml-en	897K	19.76	21.95	29.84	49.88
ta-en	428K	18.71	20.90	27.05	44.55
te-en	104K	11.92	14.57	21.17	41.98

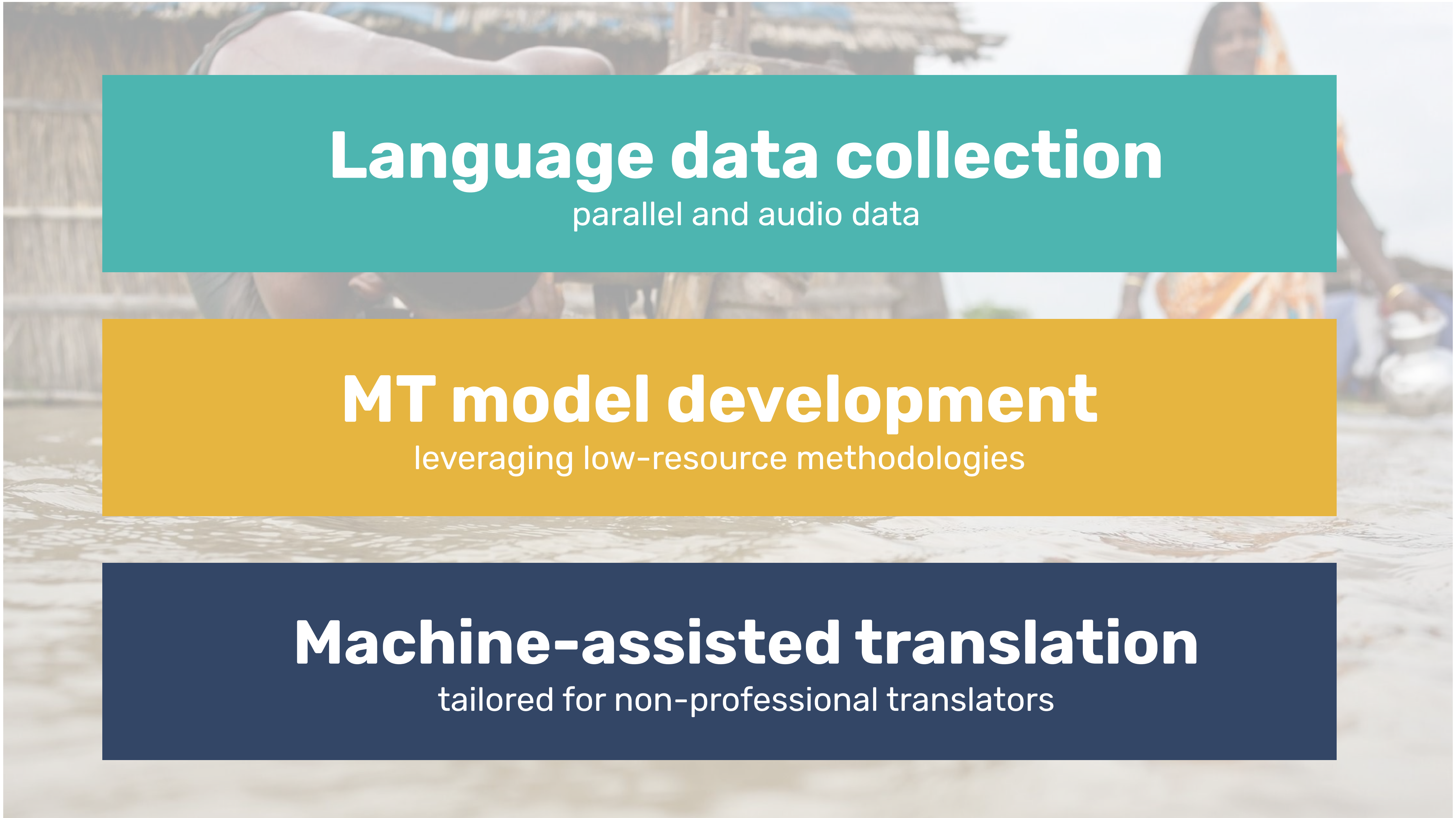
Table 2: Multi-BLEU Score with x% of partial input

Santy, Dandapat, Choudhury, Bali. "INMT: Interactive Neural Machine Translation Prediction". EMNLP 2019

Interactive Machine Translation

- Faster turnaround of document translations
  - compared to manual, and post-edited
- Human-machine collaboration to best leverage low-resource models
- Boost for hard-to-source languages
  - for translation by non-experts
  - for crowdsourced data collection

Data | MT | **Application**


Language data collection
parallel and audio data
MT model development
leveraging low-resource methodologies
Machine-assisted translation
tailored for non-professional translators


#LanguageTechnologyMatters
alp@translatorswb.org
https://translatorswithoutborders.org/
TRANSLATORS
WITHOUT BORDERS


TRANSLATORS
WITHOUT BORDERS

NMT for humanitarian impact

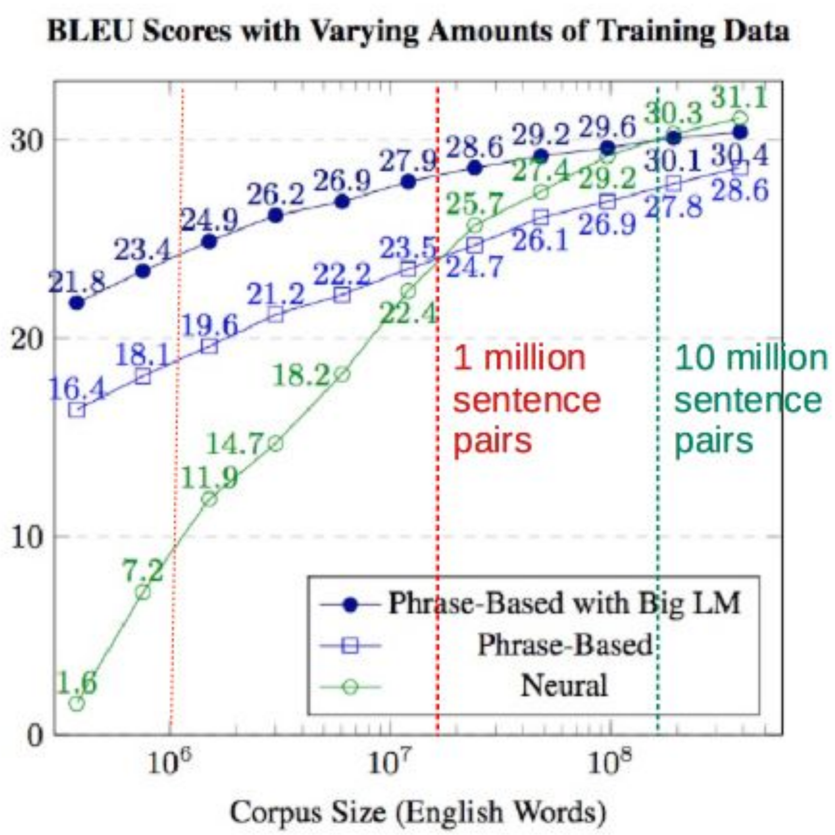


Diagram edited from Koehn and Knowles (2017)

Tigrinya NMT

SMT on 7 Ethiopian languages (Teferra Abate et al., 2018)

Parallel corpus of 300+ languages from *jw.org* (Agić and Vulić, 2019)

Available on OPUS repository (Tiedemann, 2012)

TWB's translation memories

	Ethiopian corpus	JW300	Bible-uedin	Global voices	GNOME	Tanzil	TWB	**TOTAL**
Amharic	66K	722K	61K	1.6K	57K	94K	-	1M
Ge'ez	11K	-	-	-	-	-	-	11K
Tigrinya	36K	400K	-	-	-	-	2.5K	439K

Dataset sizes (#sentences) for Ge'ez scripted languages

Data | **MT** | Application

Gamayun kits

Language	kit-5k	Audio	Language tech development goals
Hausa	✓	⚙	Machine-assisted data collection
Kanuri	✓	⚙	Machine-assisted data collection
Kurmanji Kurdish		⚙	Machine-assisted survey transcription
Rohingya	✓	✓	Glossary with voice search
Coastal Swahili	✓	✓	MT and audio keyword detection
Congolese Swahili	✓		Interactive neural machine translation
Tigrinya	⚙		Interactive neural machine translation

Data MT Application

Interactive Machine Translation

How?

- Constrained decoding on top of *OpenNMT* models
- Latest development: BPE integration
- Work-in-progress: Evaluation with our volunteer translators

Demo

- https://microsoft.github.io/inmt/

Data | MT | **Application**

BUSINESS TRANSLATION BEYOND LOCALIZATION

KIRTI VASHEE

AMTA 2020

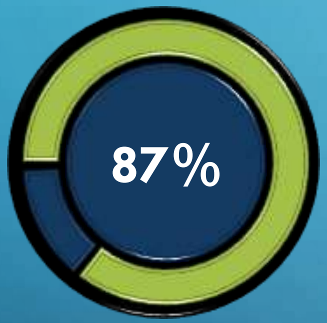
THE GLOBAL VILLAGE IS A REALITY

We are connected as never before

Content increasingly **defines the digital presence of the modern enterprise**

CONTENT **REALLY** MATTERS IN THE DIGITAL MARKETPLACE

DIGITAL TRANSFORMATION
IS THE FUEL FOR
ECONOMIC GROWTH

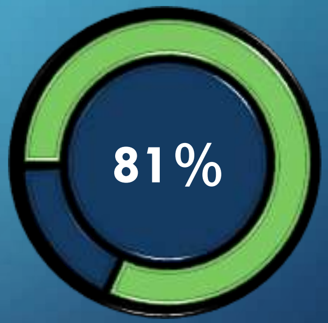


87% of companies believe digital transformation is a **competitive opportunity**

GLOBALIZATION
HAS GONE
DIGITAL

50% of the world's traded services are **delivered digitally**

SECURITY
REMAINS A
TOP CONCERN



81% of companies expressed high levels of concern over **data breaches**

3

Since 2000, 52% of companies in the Fortune 500 have either gone bankrupt, been acquired, or ceased to exist as a result of digital disruption

75% of today's S&P 500 will be replaced by 2027

Innosight Research


Large volumes of multilingual data flows have created
a huge and growing need for rapid translation

THE IMPACT OF DIGITAL TRANSFORMATION

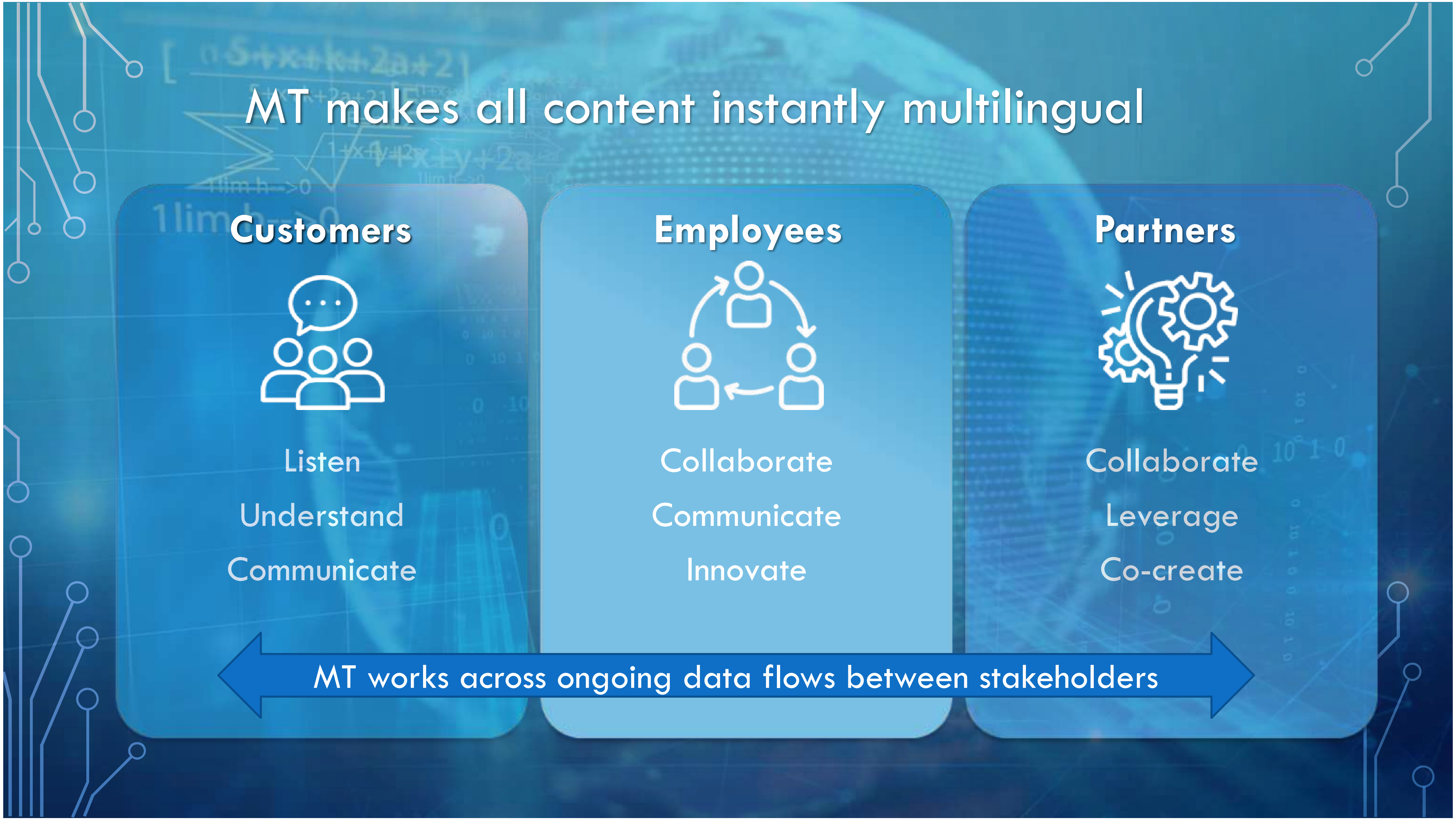
Customers expect large volumes of relevant content available across all digital channels 24/7

Content is the best salesperson for the active digitally savvy customer

Rapid response with the right content is a requirement to be digitally relevant

MT expands the reach of translation solutions into the heart of the enterprise

The potential to use unedited RAW MT continues to grow and increasingly enhances international business initiatives


MT makes all content instantly multilingual
Customers
Listen
Understand
Communicate
Employees
Collaborate
Communicate
Innovate
Partners
Collaborate
Leverage
Co-create
MT works across ongoing data flows between stakeholders

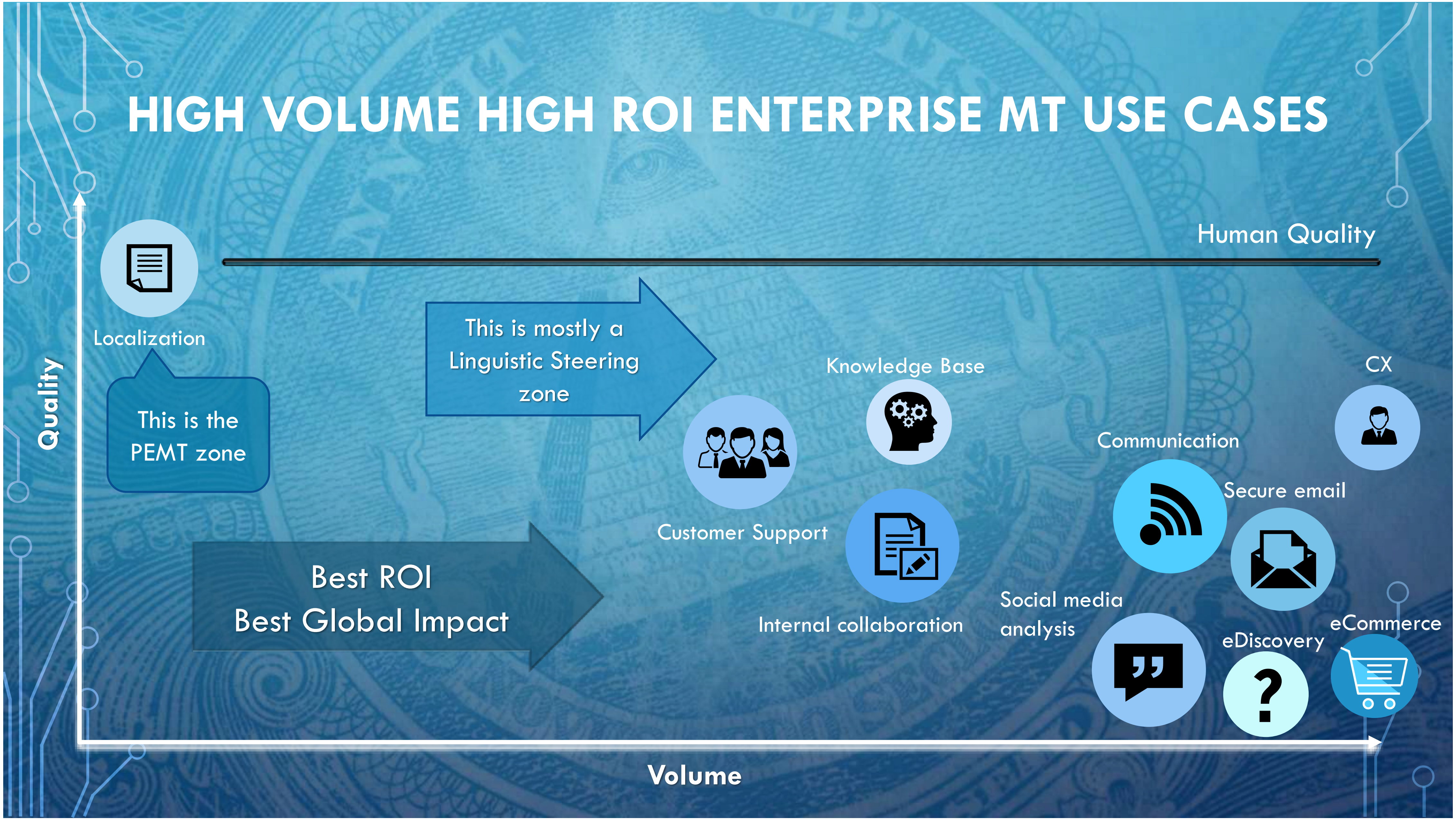
MT IN THE LOCALIZATION INDUSTRY

COST CONTAINMENT

PEMT EFFICIENCY

QUALITY MEASUREMENT

Ignores the transformational role of RAW MT when integrated with flowing enterprise content


HIGH VOLUME HIGH ROI ENTERPRISE MT USE CASES
Human Quality
Localization
This is the PEMT zone
This is mostly a Linguistic Steering zone
Best ROI
Best Global Impact
Knowledge Base
CX
Customer Support
Communication
Secure email
Internal collaboration
Social media analysis
eDiscovery
eCommerce
Quality
Volume

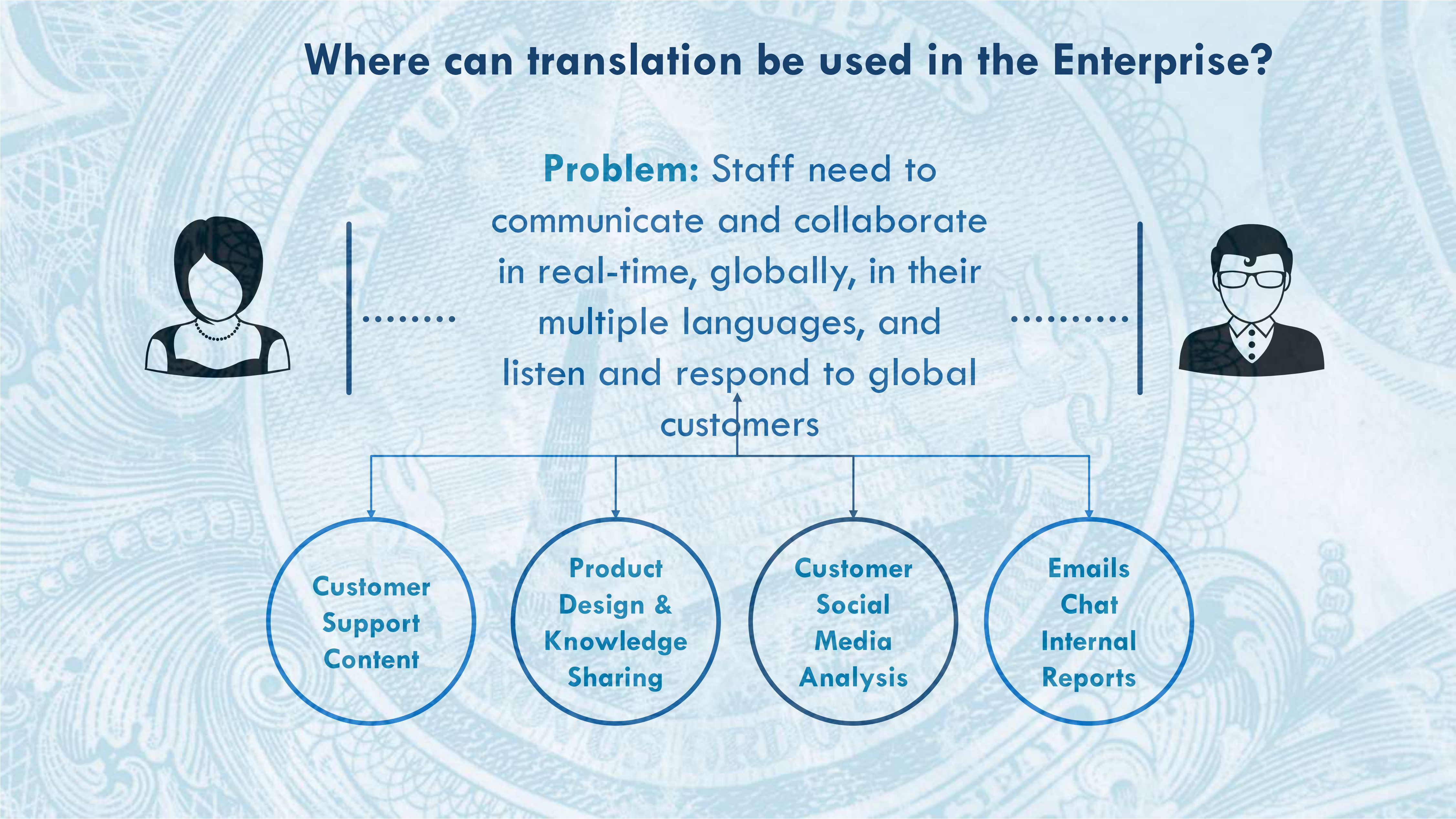
Strategic MT use cases drive us to higher level discussions that are focused on mission-critical enterprise issues
& C-Level concerns

Enterprise MT

Communication & Collaboration

Improved Global Agility & Responsiveness

Internal & External


Where can translation be used in the Enterprise?
Problem: Staff need to communicate and collaborate in real-time, globally, in their multiple languages, and listen and respond to global customers
Customer Support Content
Product Design & Knowledge Sharing
Customer Social Media Analysis
Emails Chat Internal Reports

Content drives revenue and is critical to overall customer experience

Keep Customers

- Customer service
- Technical support
- Education + adoption
- Advice + best practices
- Personalized moments
- Personalized recommendations

Get Customers

- Thought leadership
- Brand awareness
- Buying research
- Sales Guidance

Enterprise MT

Global Customer Care & Support

Enhance the Global Customer Experience

Today, email and voice are top supported interactions; email and chat are to become top interactions within 12 months
(Any device, Any channel, Always on)

Contact Center 2.0 Research Report

This corresponds with the top challenges facing today's contact centers, with companies ranking improving customer experiences and customer satisfaction in the top first and third spots, respectively.

"I love calling customer service!"
…said no customer ever.

QUALITY = DID IT SOLVE THE CUSTOMER PROBLEM

Easy
- 24/7
- Omni-channel access
- Multilingual

Fast
- Single interaction resolution
- Minimal Wait

Accurate
- Single source of truth
- Complete

Is support content available **faster** around the world?

Is it **easily found**?

Is it **useful**?


MT ENABLES BROAD GLOBAL REACH ACROSS ESCALATION TIERS
Self Service Knowledge Base
Interactive Chatbots
Multilingual Chat Enabled Live Agents
Translating millions of words in real-time without editing

Enterprise MT

eCommerce

Making Product Catalogues Global


eCommerce is one of the biggest transformations of commercial business practice in history

Multilingual eCommerce
Online eCommerce Product Portfolios
Allow rapid expansion of global buyers with multilingual Product Catalogues
Rapidly expand global customer base
Expand into global markets in a cost effective way
Product Title
Product Description
Global User Reviews
Buyer <> Seller Communications
Transaction Related Pricing, Policies & Procedures

ECOMMERCE: THE FASTEST ACCESS TO THE GLOBAL MARKET

Top-Tier Markets	Second Wave	Wait and See
United States United Kingdom China Japan South Korea Australia	India Indonesia Mexico Brazil Saudi Arabia Sweden Switzerland	Russia Argentina South Africa Nigeria

Source: Shopify

UNDERSTANDING MT QUALITY IN USE CONTEXT

Consumer Experience, Communication & Collaboration, eDiscovery

High translation volume:
10s of **millions** of words per day

Larger budgets > Accelerate global business agility & response

Limited post-editing possible

Linguistic steering and moderate customization produce positive outcomes

Localization

Low translation volume:
10s of **thousands** of words per day

Small budgets > Improve efficiency, reduce cost

Post-editing is critical

Requires deep, costly customization to enable positive PEMT outcomes

LINGUISTIC STEERING VS POST EDITING

CX, Communication, Global Collaboration eCommerce eDiscovery use cases

Millions of words a day with little human touch: Real-time

Corpus and linguistic pattern level focus & linguistic feedback

Big Data Orientation

Localization Use Case

Thousands of words a day with multiple levels of human touch

Sentence level focus: Batch

PEMT focused culture

Published Content Orientation

LINGUISTIC STEERING VS POST EDITING

CX, Communication, Collaboration eCommerce/eDiscovery use cases

Millions of words a day

Massive volumes of unstructured content
Mission-critical data flow
Broad coverage encompassing all enterprise departments

Localization use case

Thousands of words a day

Small volumes of structured and controlled content
Necessary for regulatory compliance-related data flows
Basic product documentation and high-level marketing and support content

The Translation Opportunity Beyond Localization

Develop large-scale translation ability

- Understand Linguistic Steering vs PEMT
- Understand how to solve dynamic, big-data translation challenges
- Understand corpus level linguistic profiling
- Identify internal and external high value content

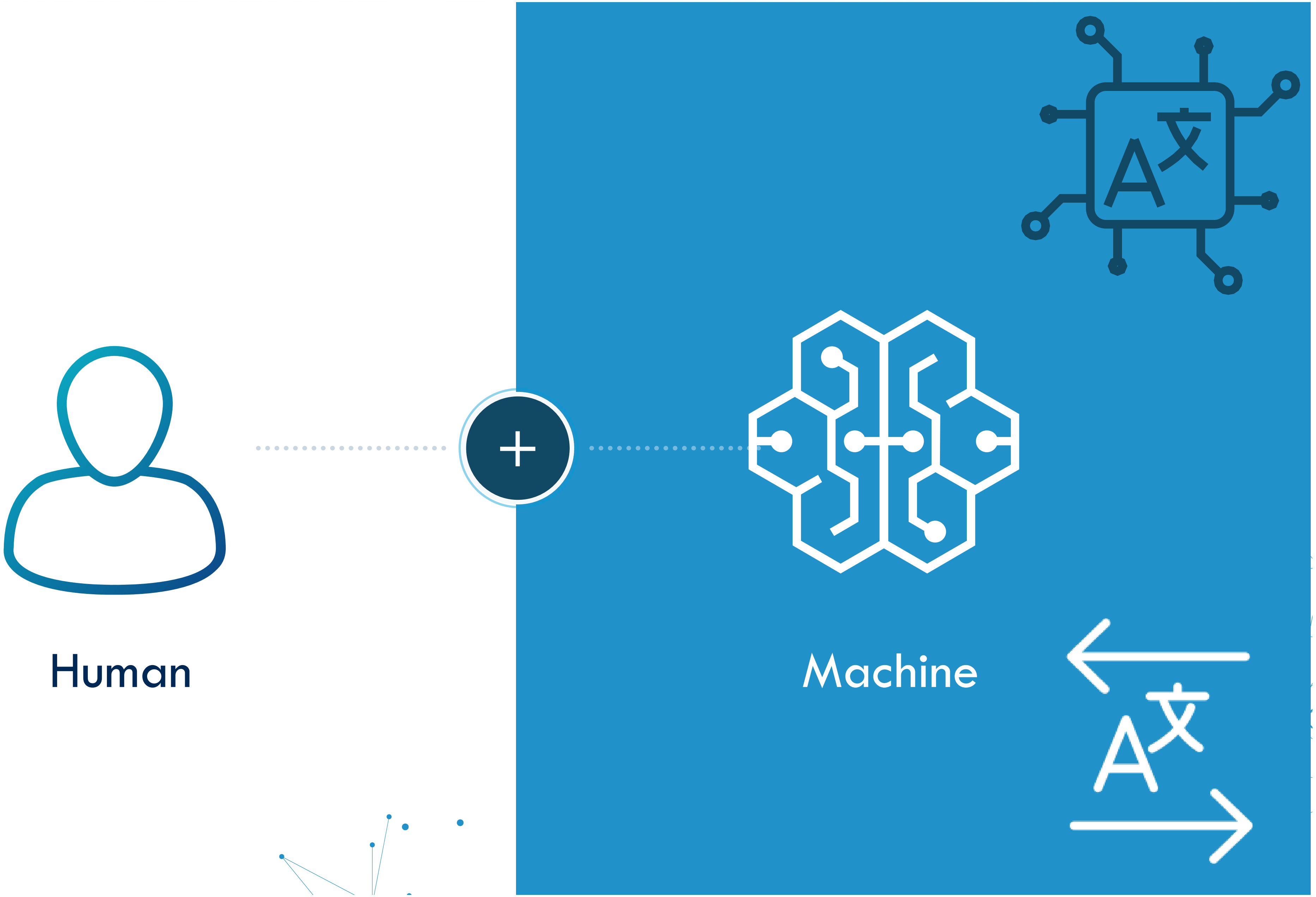
Leverage multilingual content production

Looking at Opportunity Beyond Localization

Focus on the metrics that matter most

- Enhanced global communication and collaboration
- Expanded coverage & rapidity of response in global customer service/support scenarios
- Identify & Understand what customers care about across the globe
- Improved conversion rates in eCommerce

Improve the Customer Digital Experience


Human
Machine

KIRTI VASHEE

eMpTy Pages Blog: HTTPS://kv-emptypages.blogspot.com/

@kvashee

Thank You

Predictive Translation Memory in the Wild: A Study of Interactive Machine Translation Use on Lilt

Geza Kovacs
geza@lilt.com

LILT

Why Interactive MT?

- **Problem**: MT systems cannot guarantee correctness. Errors can affect business reputation
- A **human in the loop** is needed to ensure correctness
- **Interactive MT**: optimizing interactions between the translator and MT system

Post-editing:
Translators edit MT output

An idea with a long history (Bisbey and Kay 1972)

Post-editing: Translators edit MT output

Source text

The physicist Arthur Eddington drew on Borel's image further in The Nature of the Physical World (1928), writing: If I let my fingers wander idly over the keys of a typewriter it might happen that my screed made an intelligible sentence.

MT suggestion

Le physicien Arthur Eddington a attiré sur l'image de Borel dans le caractère du monde physique (1928), écrit: Si je laisse mes doigts se promener les bras croisés sur les touches de la machine à écrire, il peut arriver que mon chape fait une phrase intelligible.

Submit

Image Source

Green, Spence, Jeffrey Heer, and Christopher D. Manning. "The efficacy of human post-editing for language translation." *Proceedings of the SIGCHI conference on human factors in computing systems*. 2013.

Post-editing: Translators edit MT output

Pros

- Easy to implement (can use off-the-shelf MT system)
- Reduces translation time [1]

Cons

- Post-edited text is more similar to MT than unassisted translations [1]
- Translators can find post-editing frustrating [2]

[1] Green, Spence, Jeffrey Heer, and Christopher D. Manning. "The efficacy of human post-editing for language translation." *Proceedings of the SIGCHI conference on human factors in computing systems*. 2013.
[2] Gaspari, Federico, et al. "Perception vs reality: Measuring machine translation post-editing productivity." *Proceedings of the 11th Conference of the Association for Machine Translation in the Americas: Workshop on Post-Editing Technology and Practice (WPTP3)*. Vancouver: AMTA, 2014.

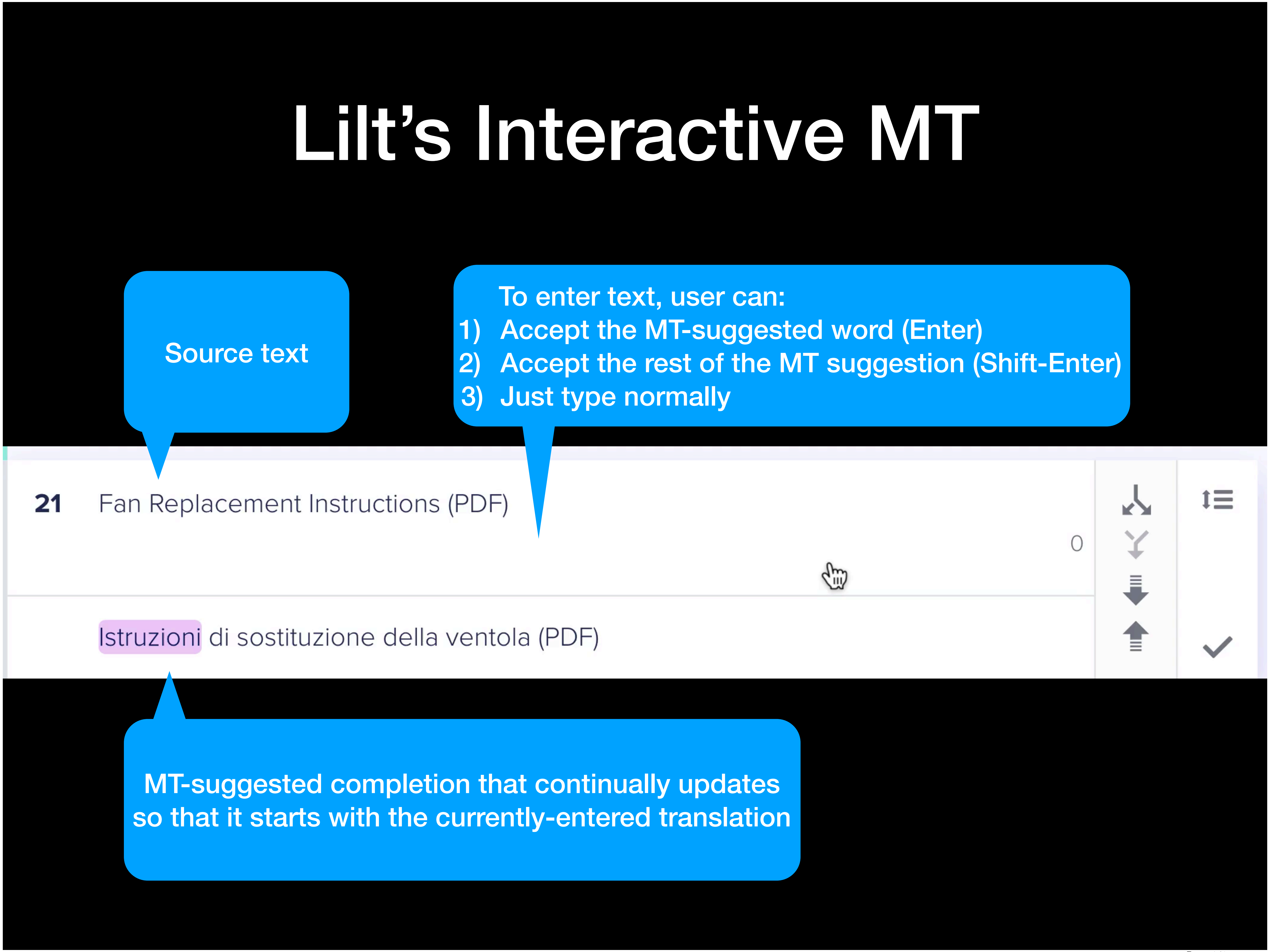
Predictive Translation Memory

MT system suggests text predictions that complete the translation the user has already entered

If the MT suggestion is correct, user can accept it; if it isn't, user can type as normal.

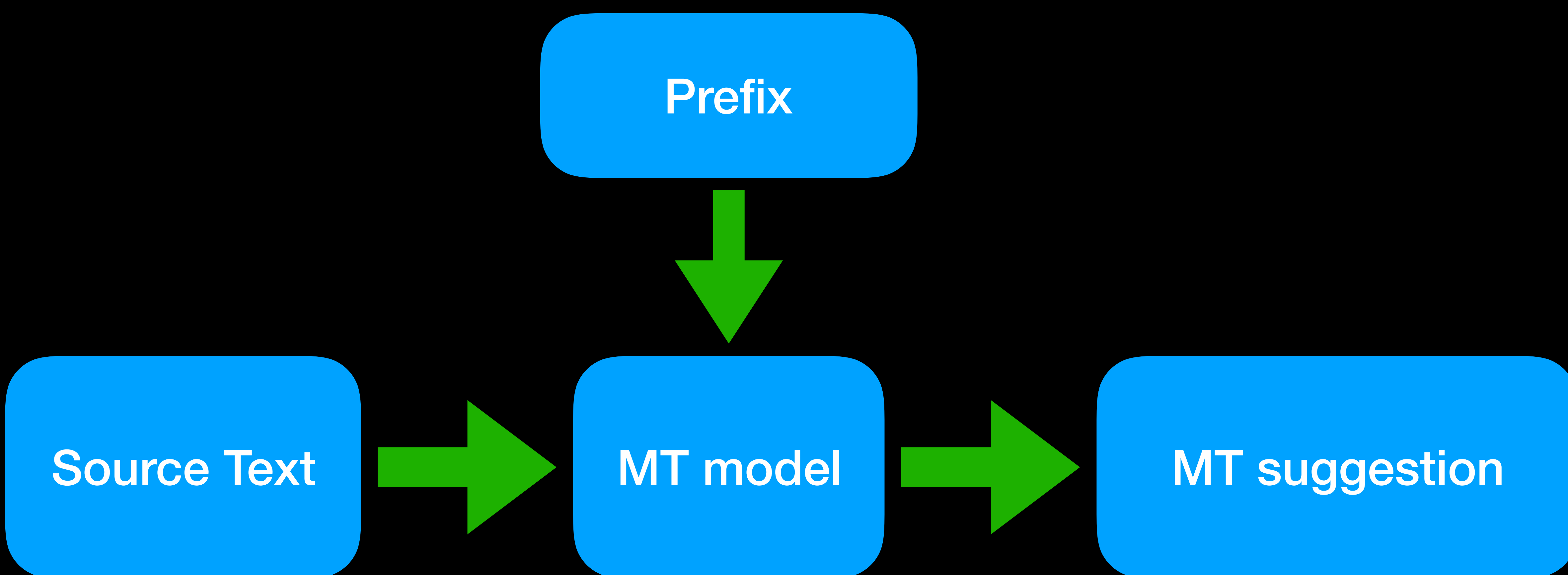
MT suggestions update and improve as users type.

Transtype (Foster 2000)


Lilt’s Interactive MT
Source text
To enter text, user can:
1) Accept the MT-suggested word (Enter)
2) Accept the rest of the MT suggestion (Shift-Enter)
3) Just type normally
21
Fan Replacement Instructions (PDF)
0
Istruzioni di sostituzione della ventola (PDF)
MT-suggested completion that continually updates so that it starts with the currently-entered translation

Interactive MT Implementation

Prefix-constrained MT model (based on Transformer architecture). Details at lilt.com/research



Interactive MT Implementation

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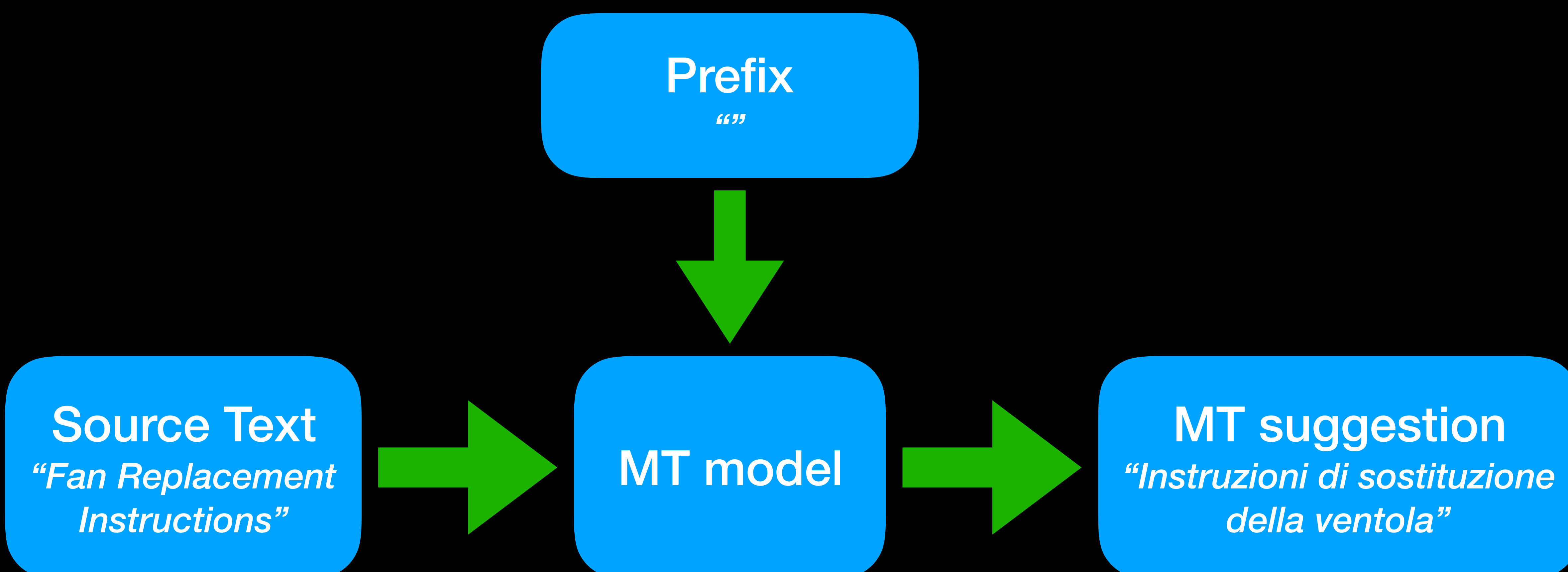

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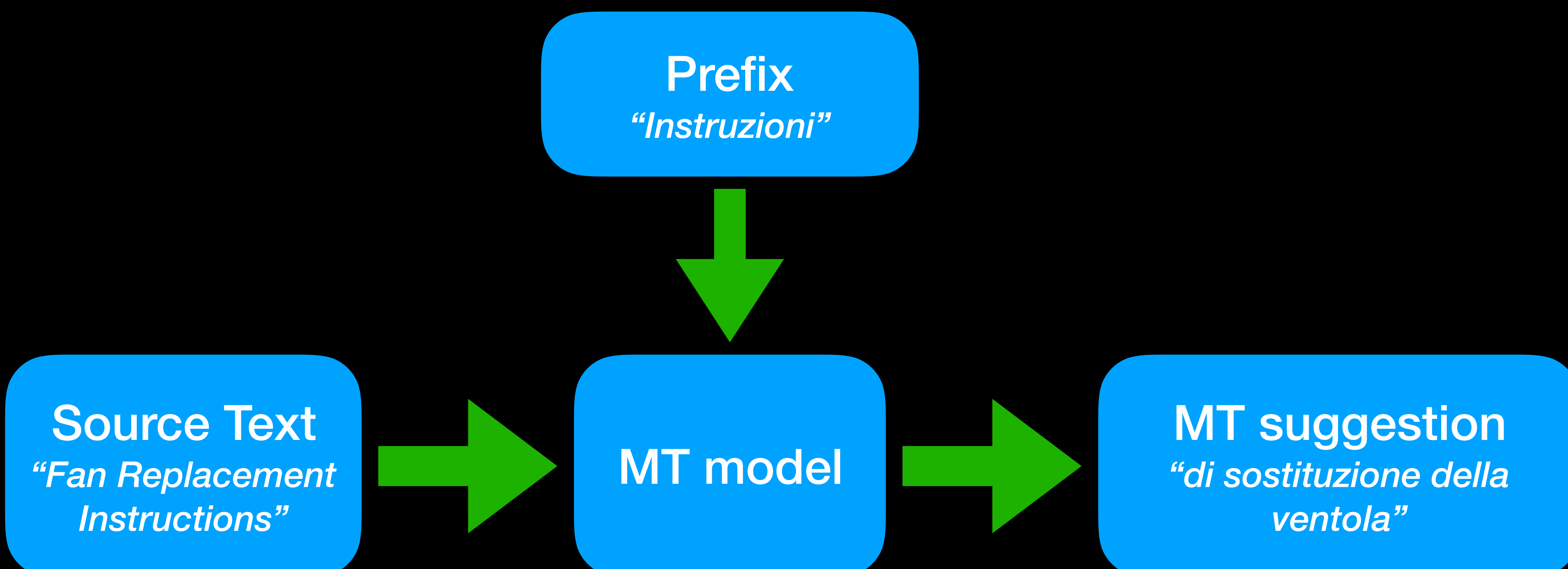

Interactive MT Implementation

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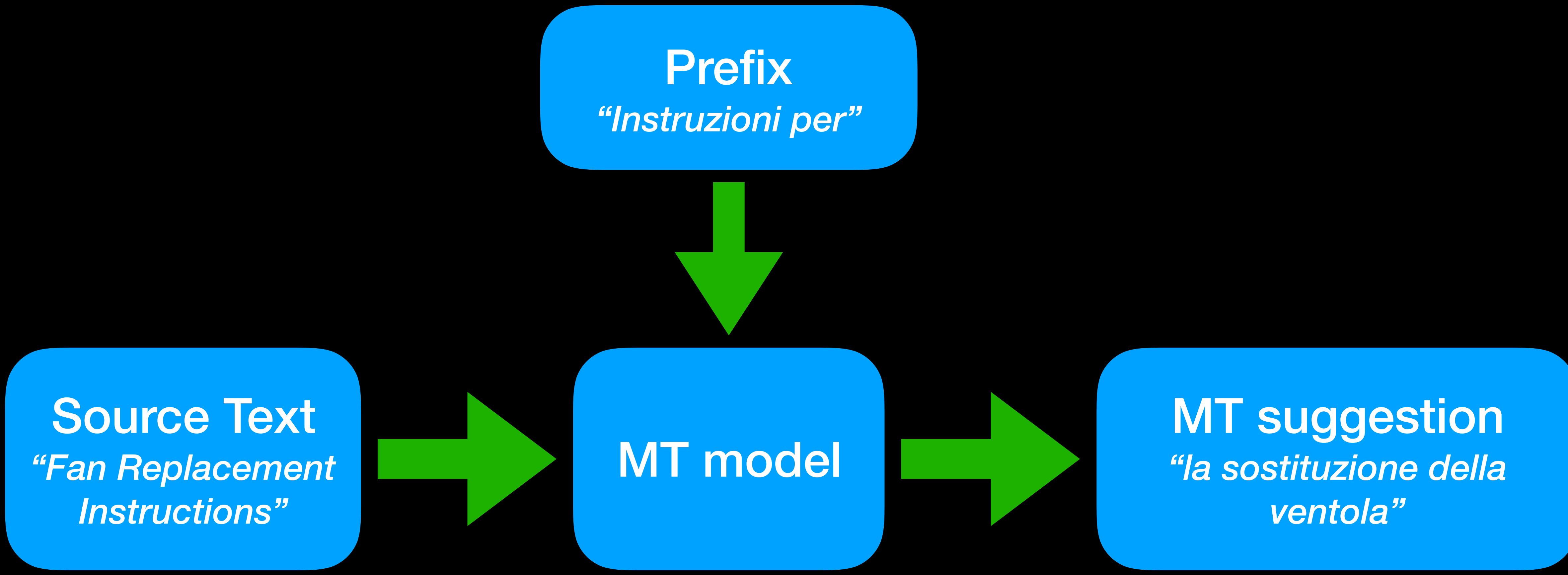

Interactive MT Implementation

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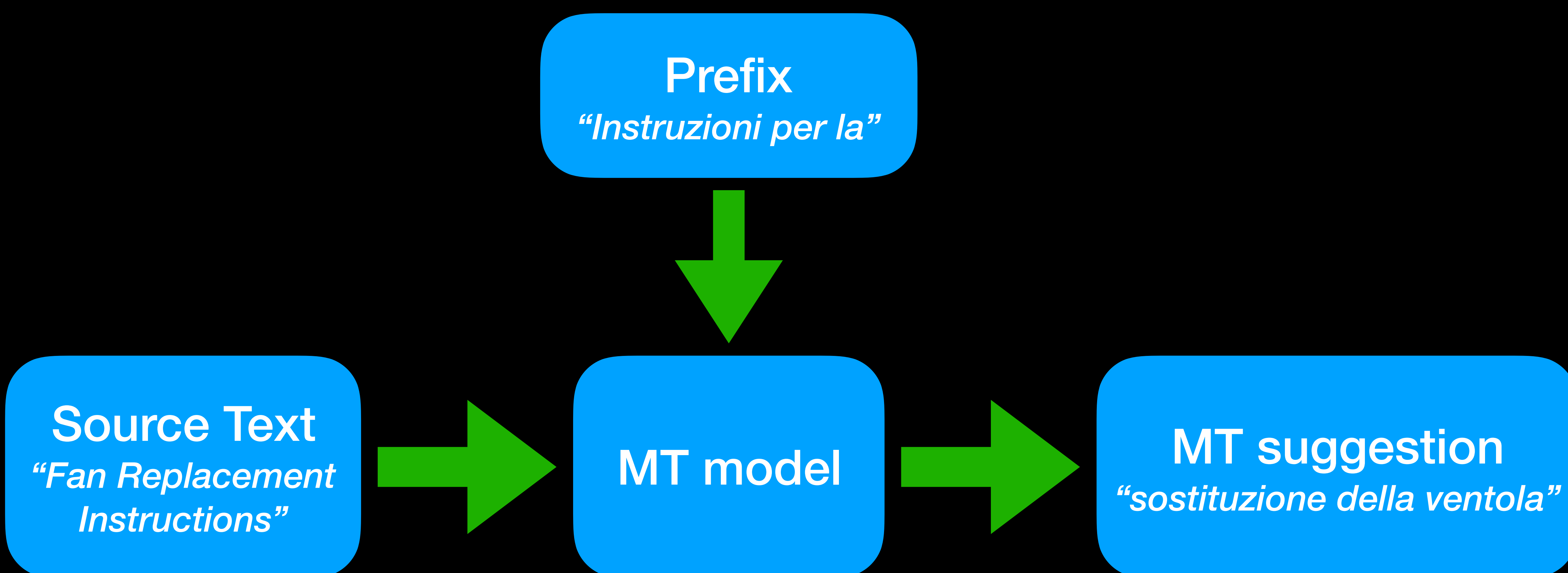

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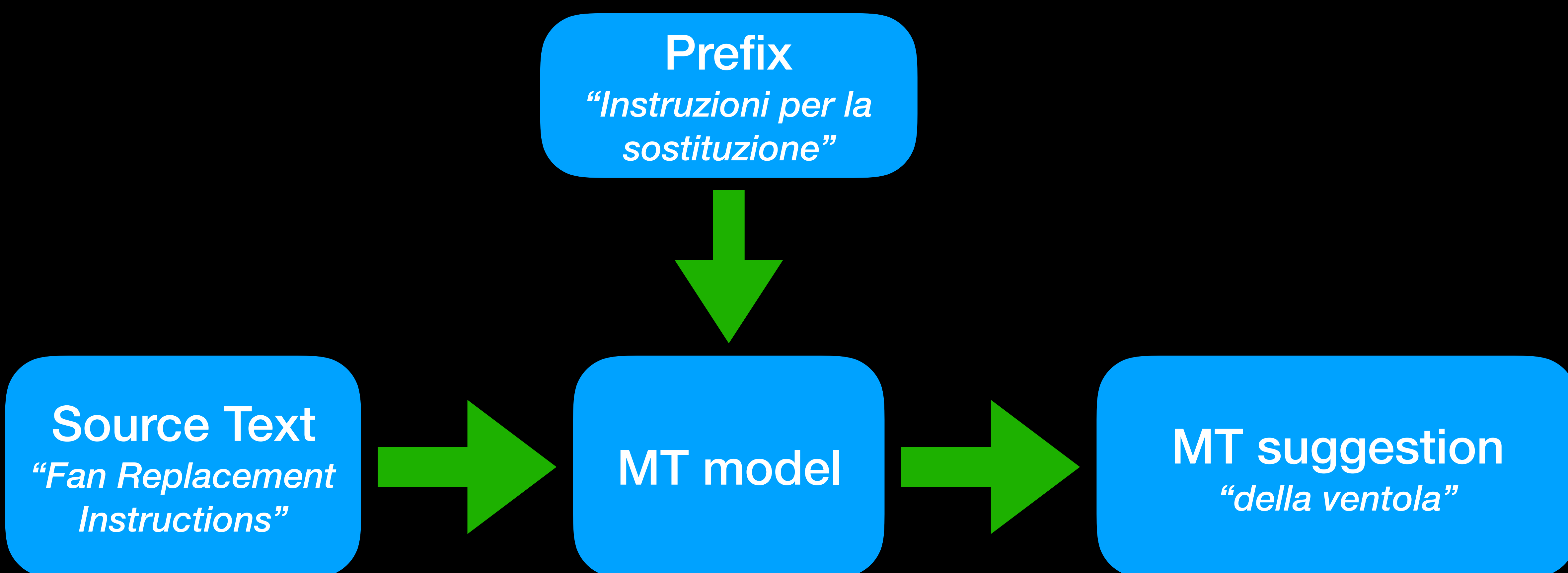

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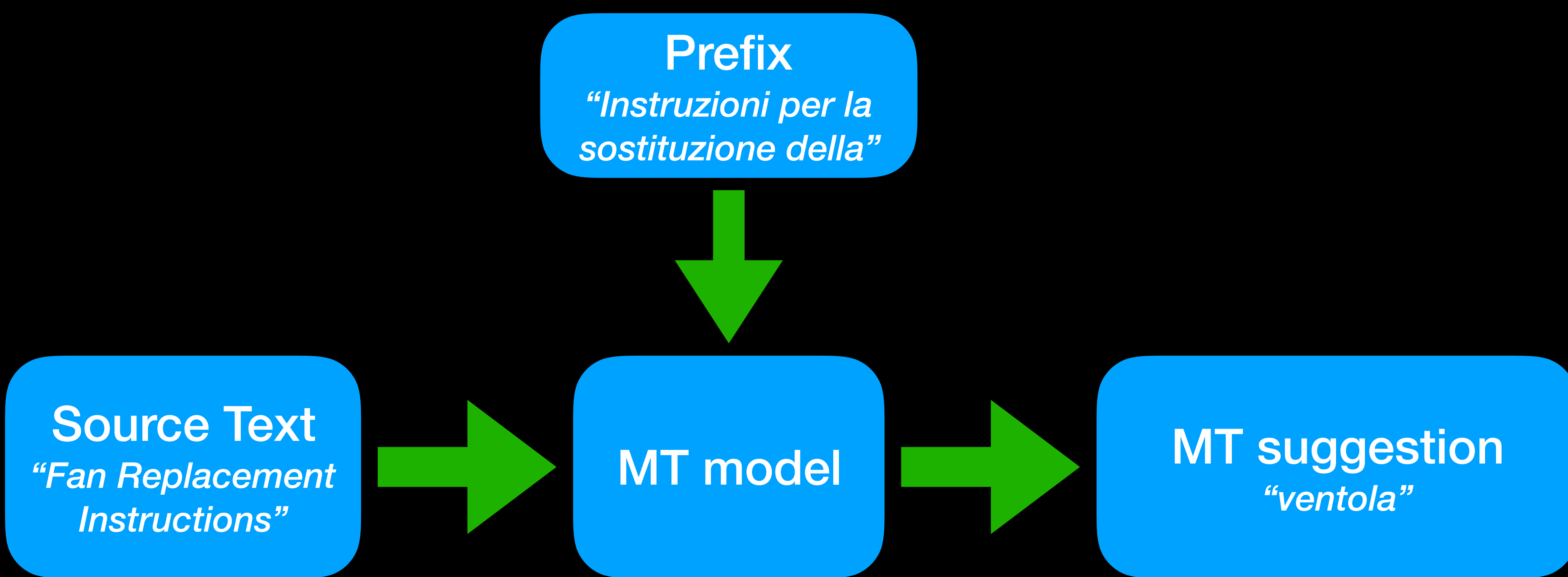
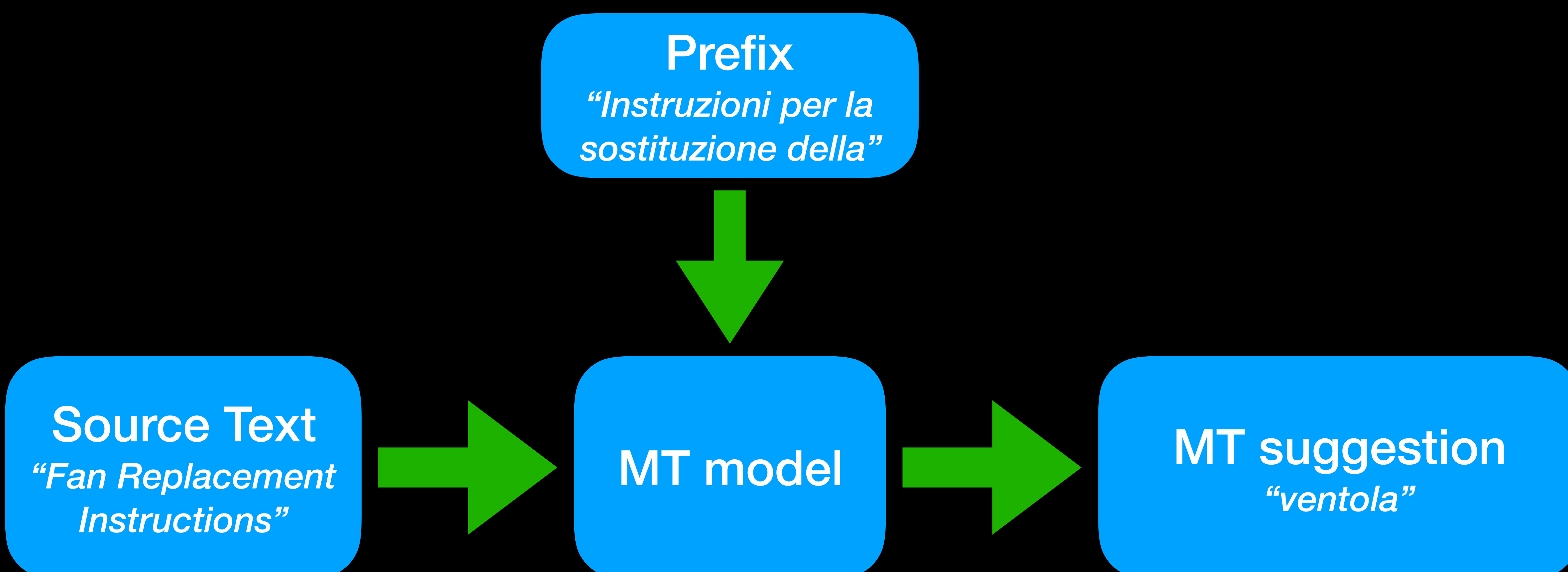
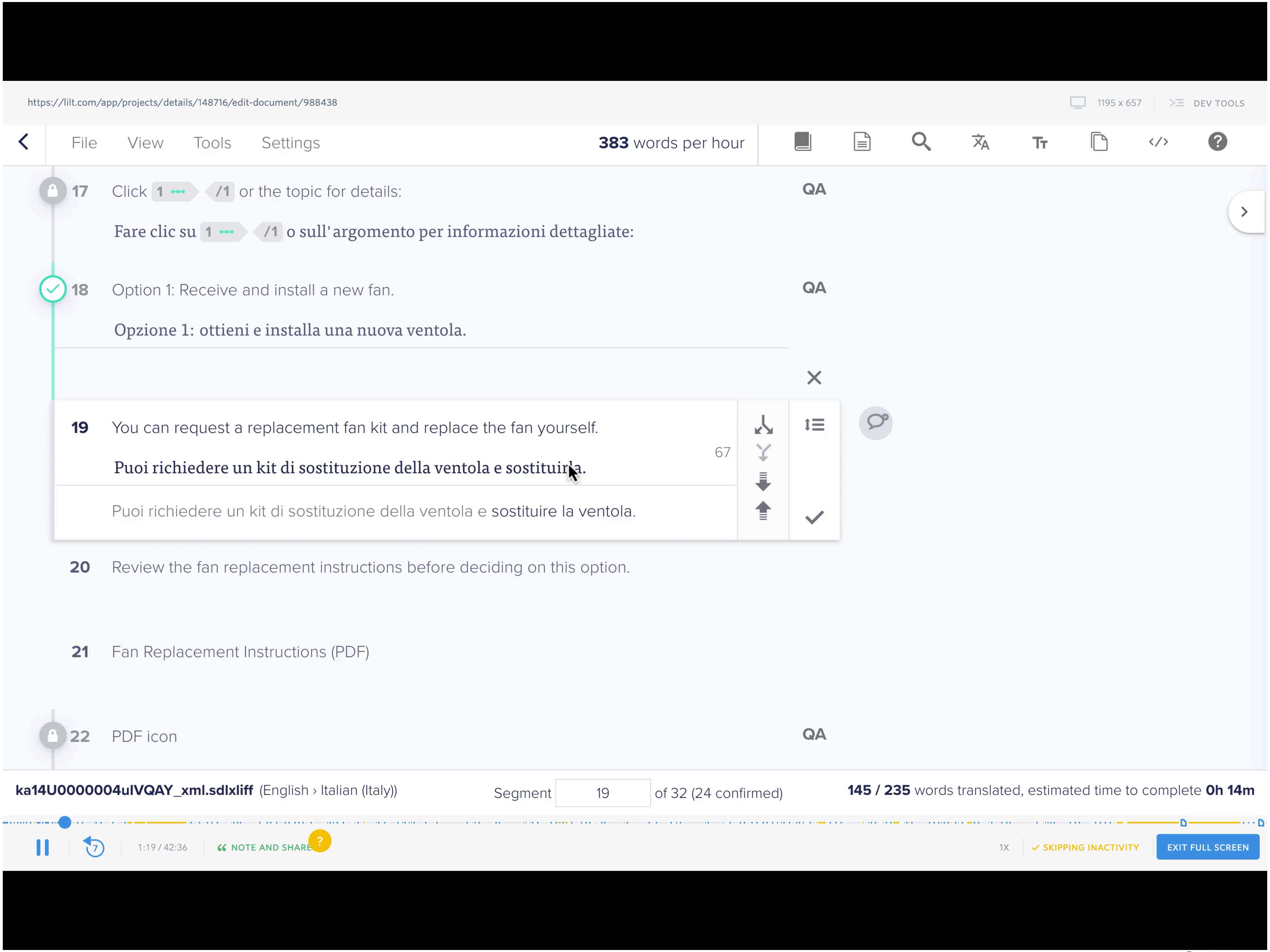


Interactive MT needs to be fast

New MT suggestion needs to be computed whenever the user’s entered text no longer matches the MT prediction.

90% of our MT requests are computed in less than 500ms




https://lilt.com/app/projects/details/148716/edit-document/988438
1195 x 657
DEV TOOLS
File
View
Tools
Settings
383 words per hour
17
Click 1 /1 or the topic for details:
Fare clic su 1 /1 o sull'argomento per informazioni dettagliate:
QA
18
Option 1: Receive and install a new fan.
Opzione 1: ottieni e installa una nuova ventola.
QA
19
You can request a replacement fan kit and replace the fan yourself.
Puoi richiedere un kit di sostituzione della ventola e sostituirla.
67
Puoi richiedere un kit di sostituzione della ventola e sostituire la ventola.
20
Review the fan replacement instructions before deciding on this option.
21
Fan Replacement Instructions (PDF)
22
PDF icon
QA
ka14U0000004uIVQAY_xml.sdlxliff (English › Italian (Italy))
Segment 19 of 32 (24 confirmed)
145 / 235 words translated, estimated time to complete 0h 14m
1:19 / 42:36
NOTE AND SHARE
1X
SKIPPING INACTIVITY
EXIT FULL SCREEN

How helpful is Lilt's Interactive MT?

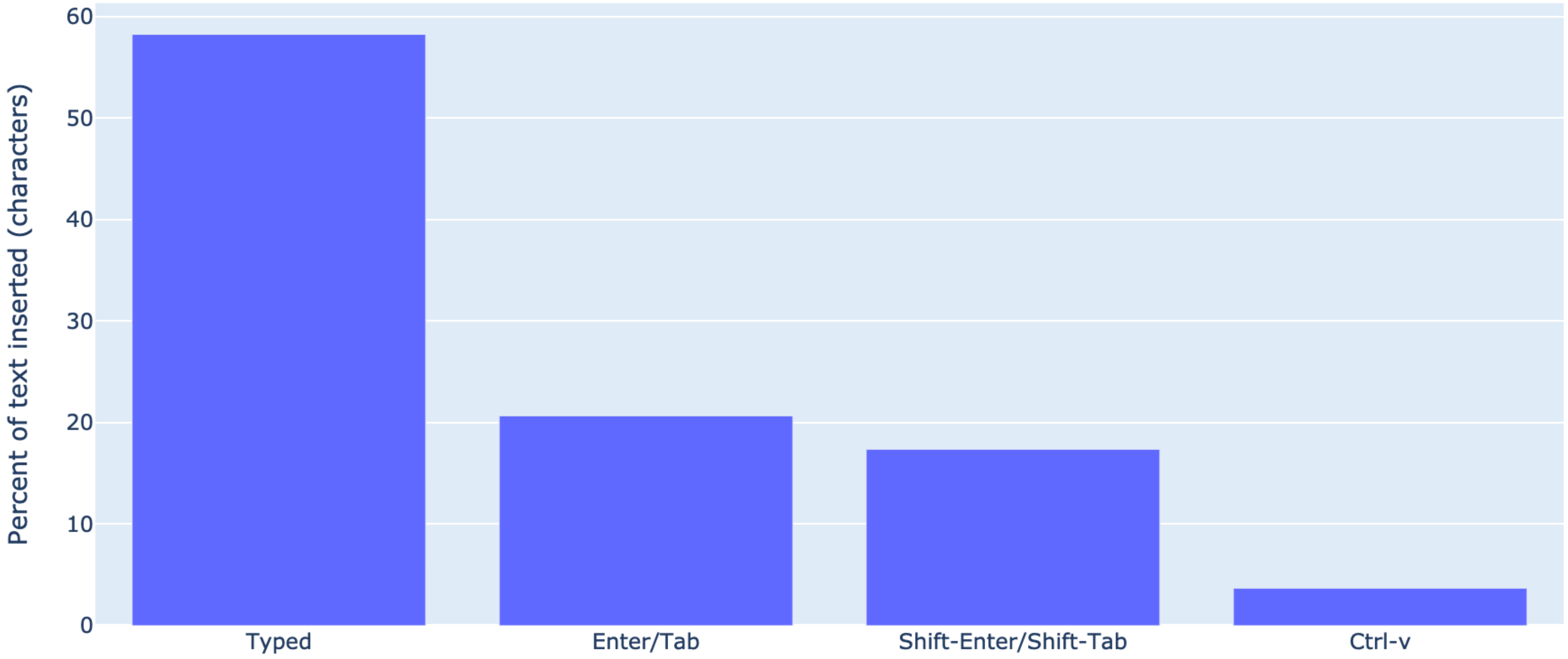
- How often do translators use our MT suggestions?
- How often are our MT suggestions available and correct?
- How much do translators use our word-level suggestions, and how much do they post-edit?
- How do translators spend time on Lilt?

How often do translators use our MT suggestions?

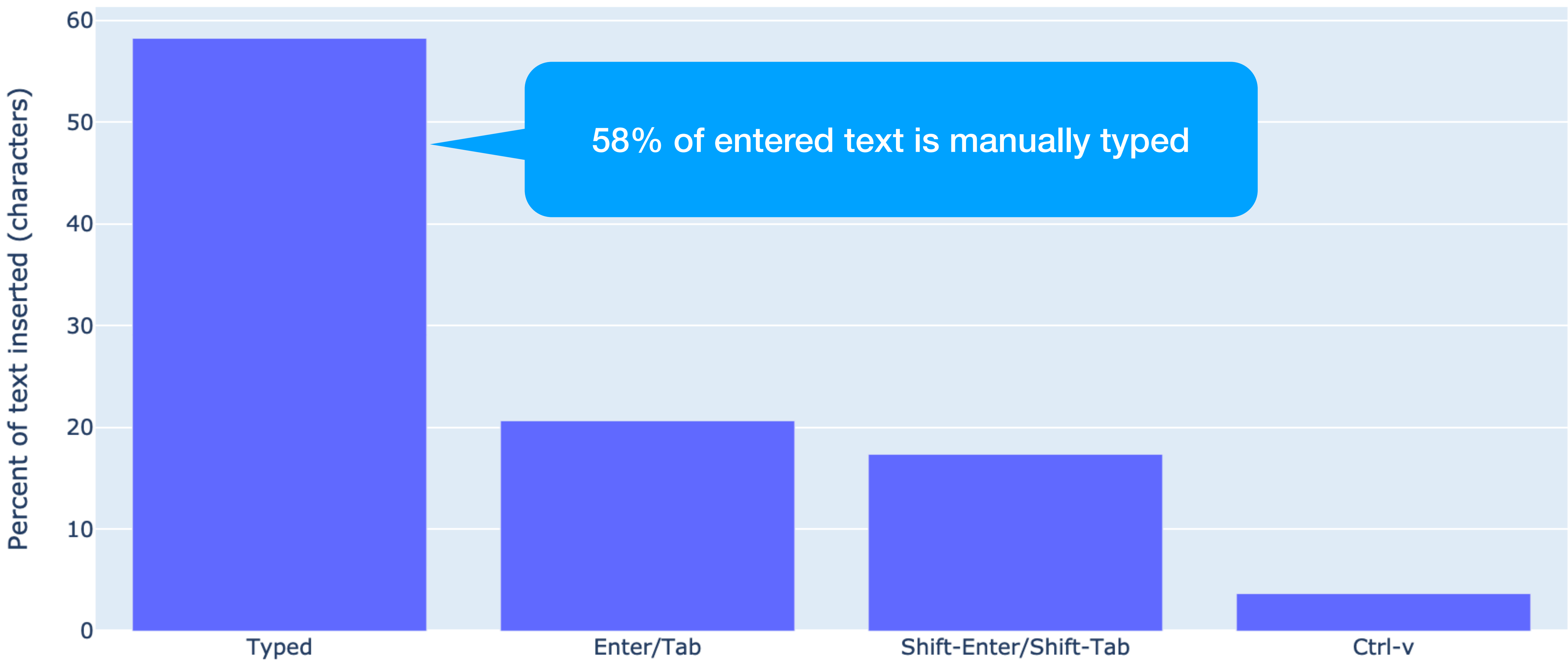
- Check how much text is inserted via Enter and Shift-Enter
- Data is from August to September 2020
- We consider only newly-generated* segments

*newly-generated segments = no TM matches, no segments majority copy-pasted

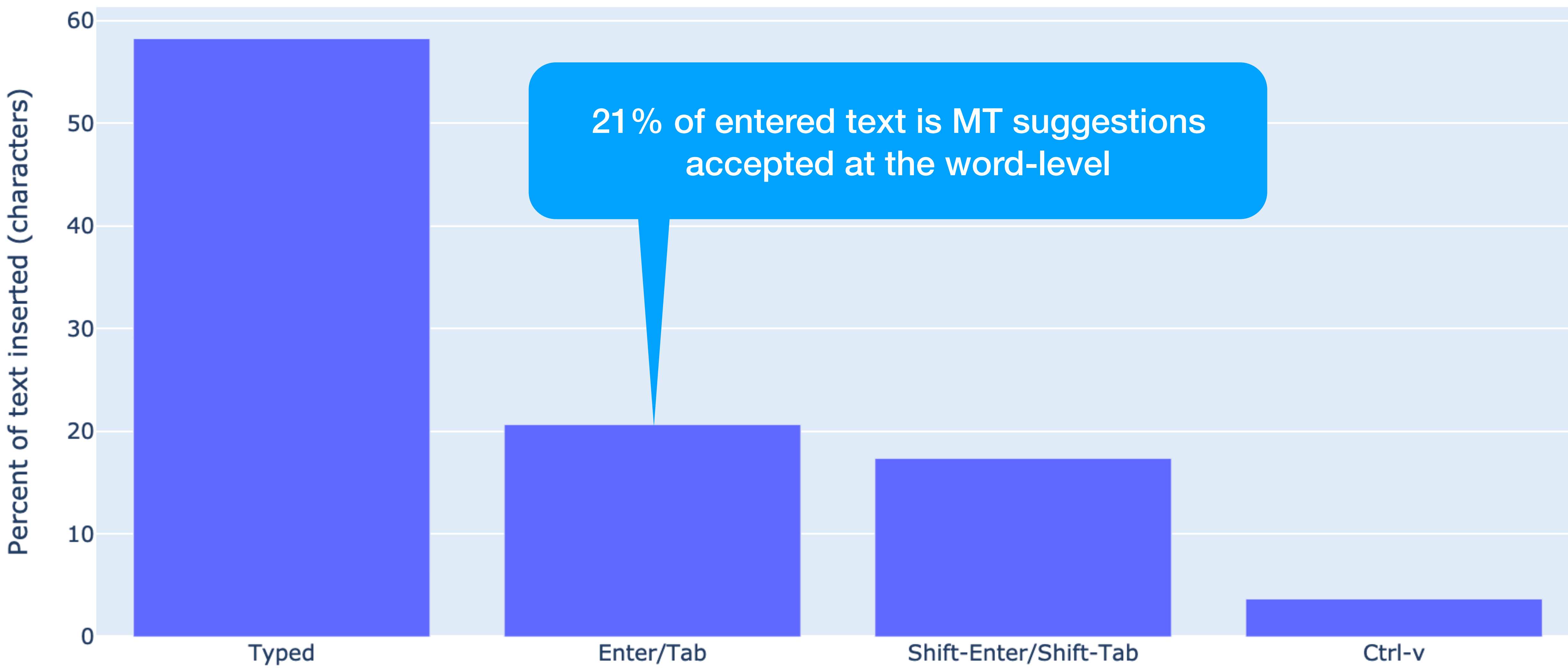
Keys through which text is inserted



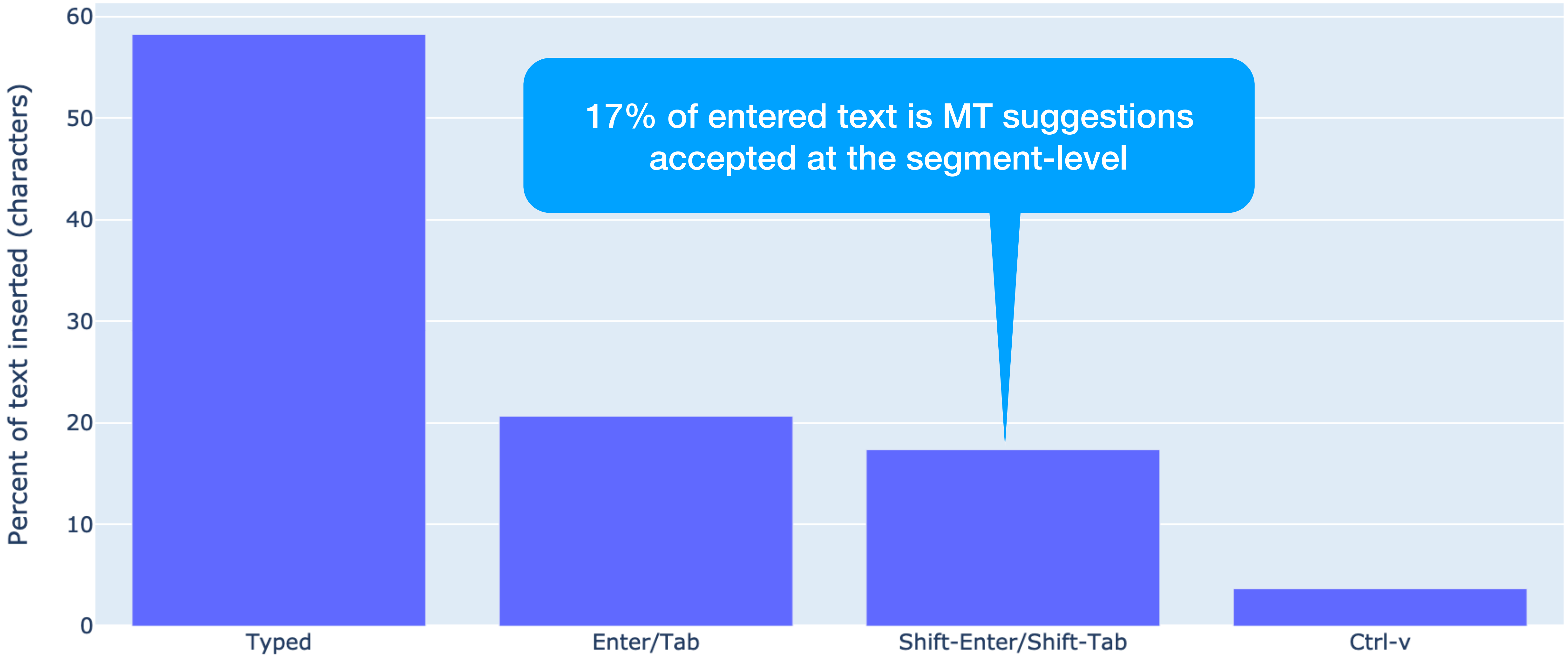
Keys through which text is inserted



Keys through which text is inserted



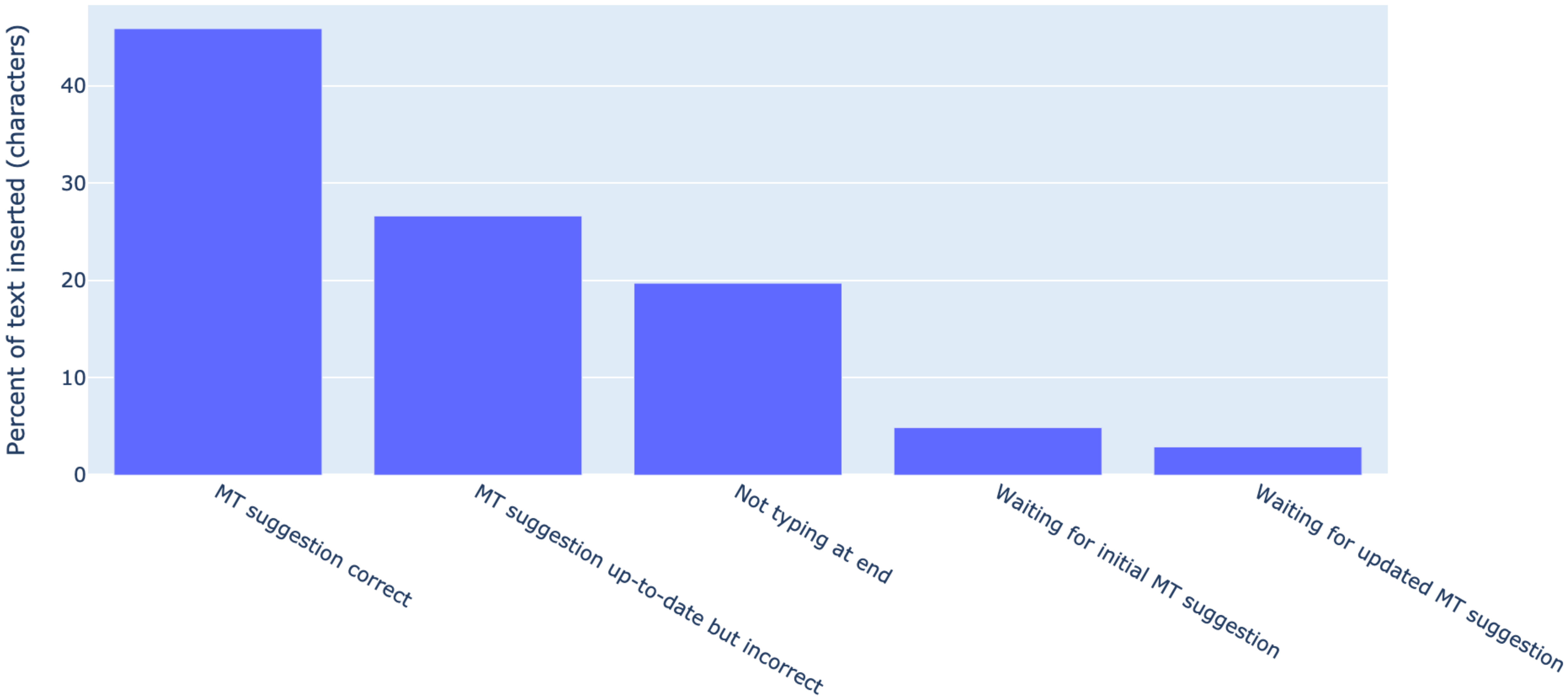
Keys through which text is inserted



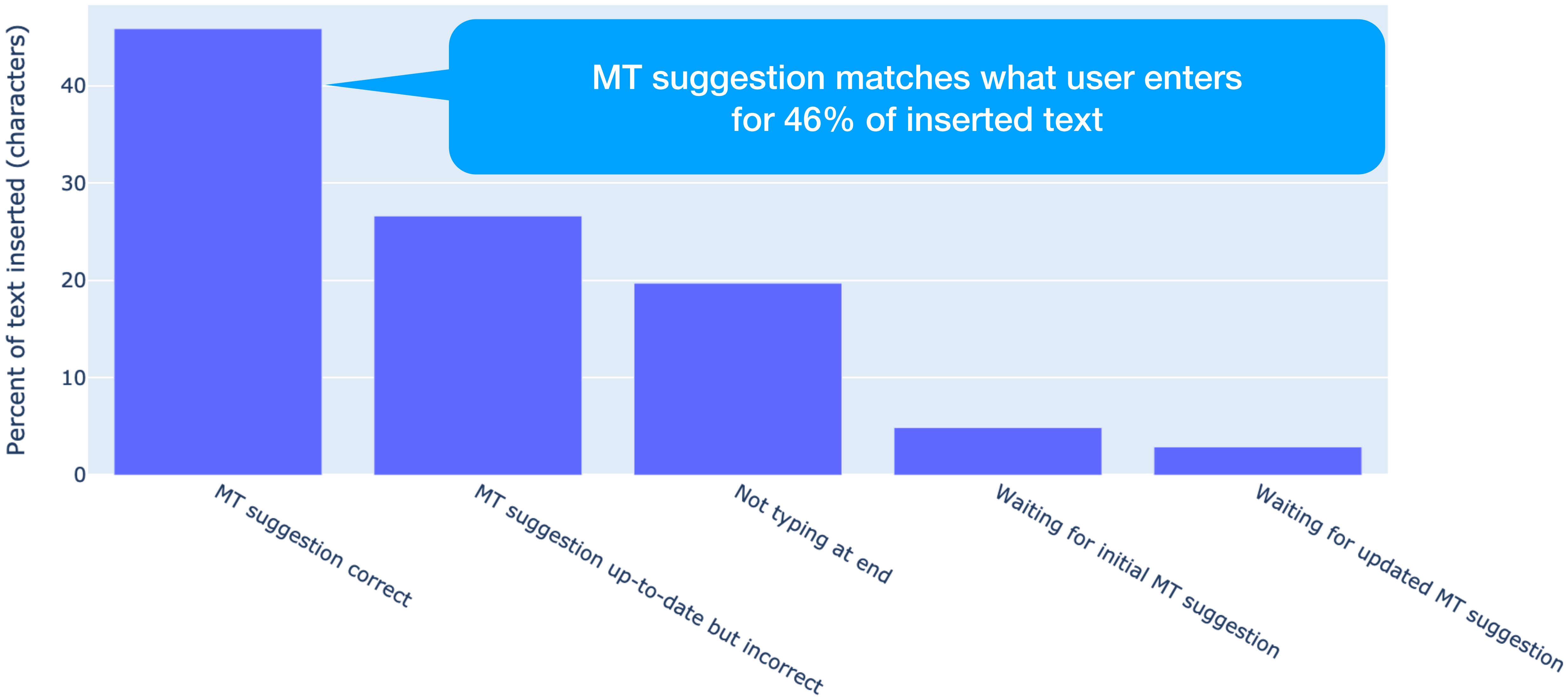
Why aren't translators using our MT suggestions more?

- Maybe translators aren't aware they can press Enter?
- Maybe they aren't editing at the end of the segment?
- Maybe the MT suggestion takes too long to show up?
- Maybe the MT suggestions don't match what the translator wants to type?

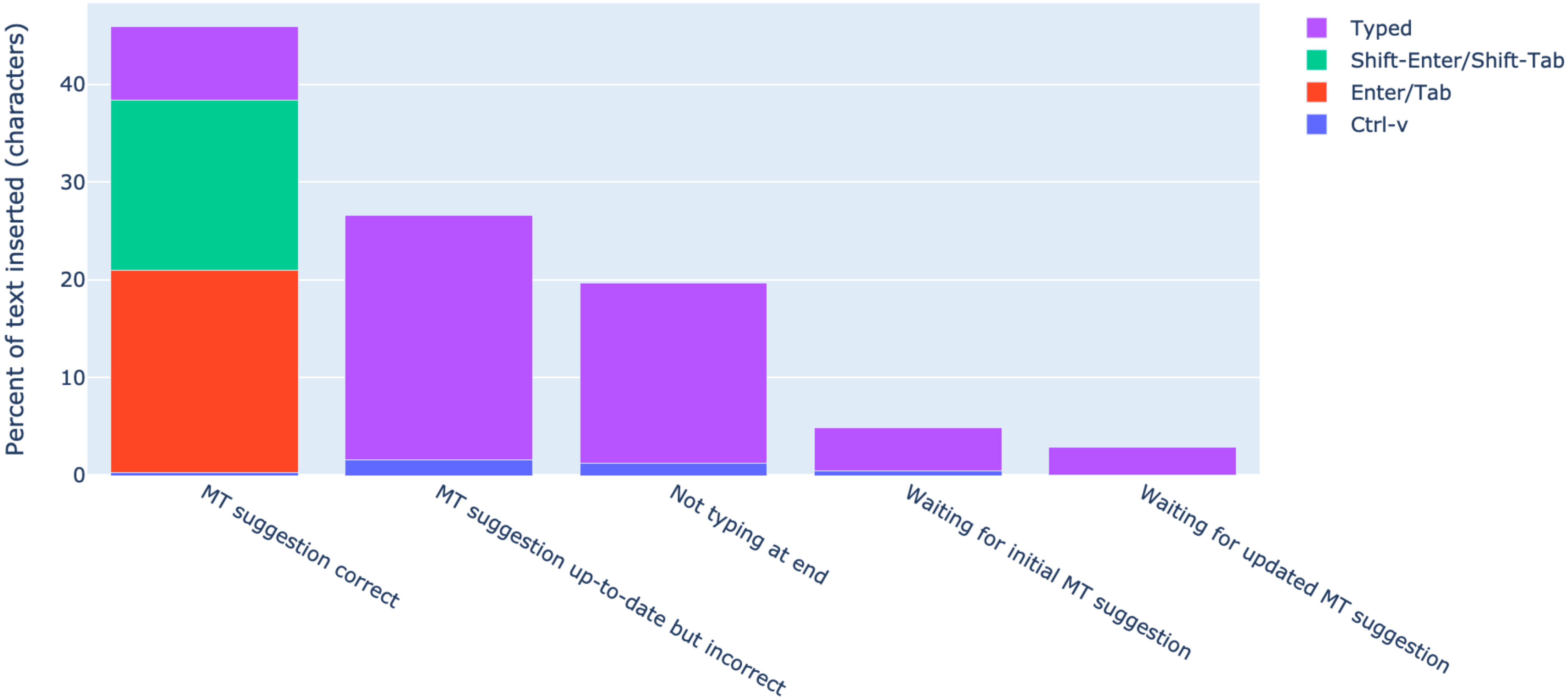
How often are our MT suggestions available and correct?



How often are our MT suggestions available and correct?



How often are our MT suggestions available and correct?



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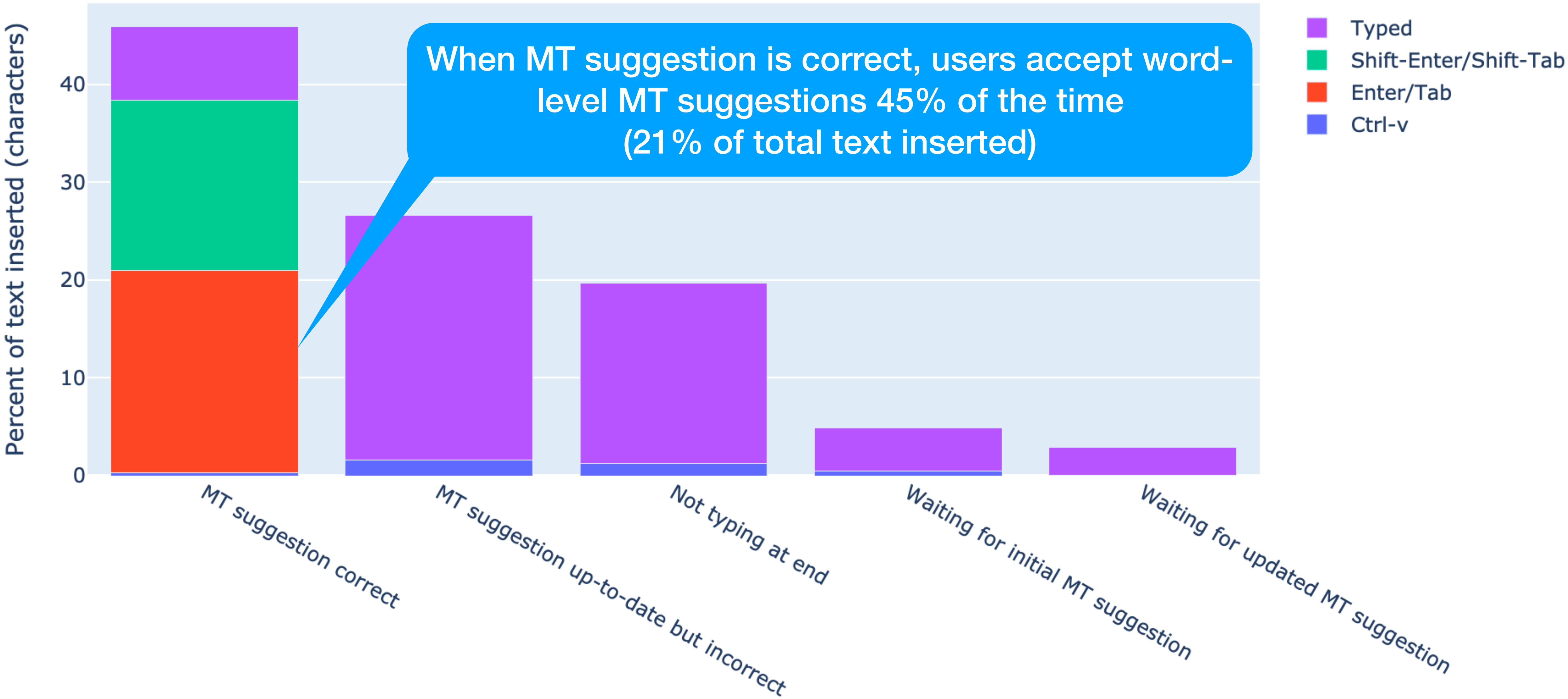
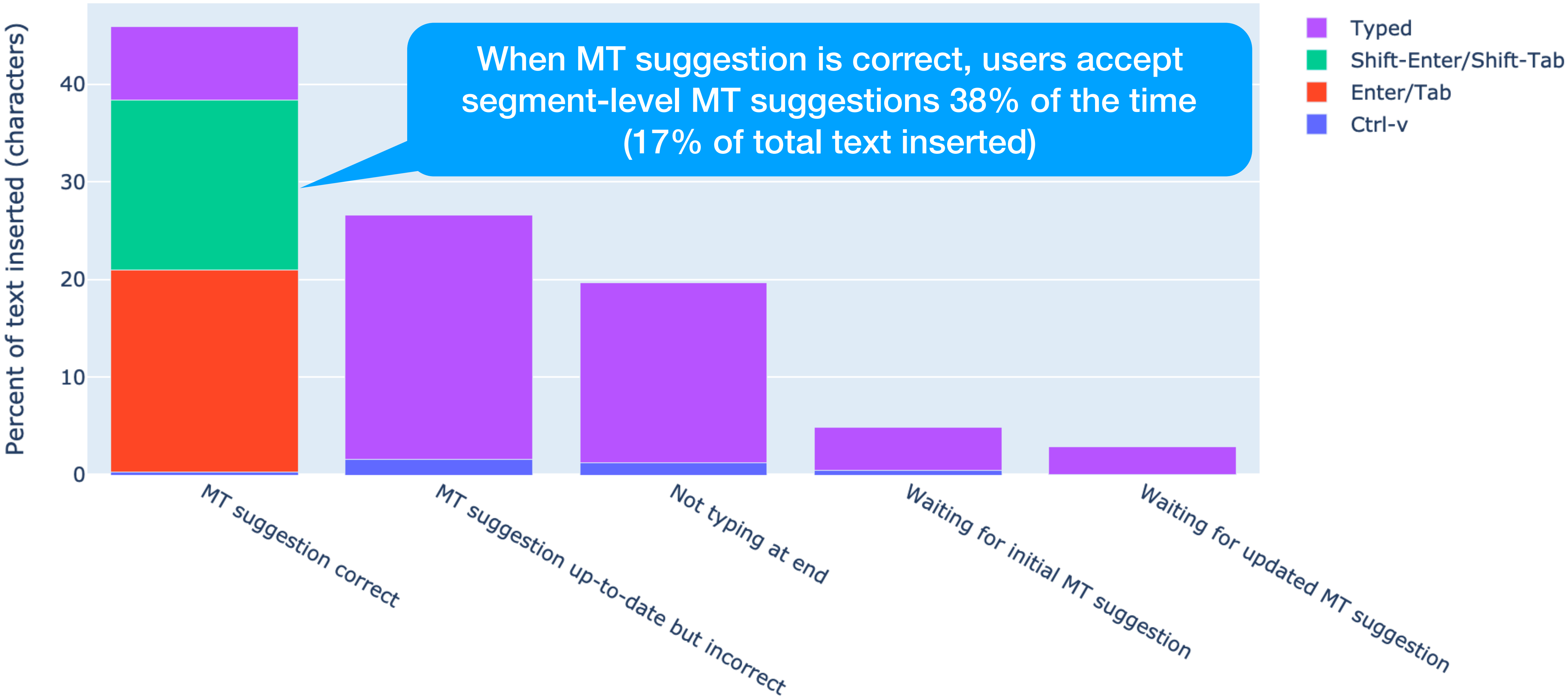


How often are our MT suggestions available and correct?



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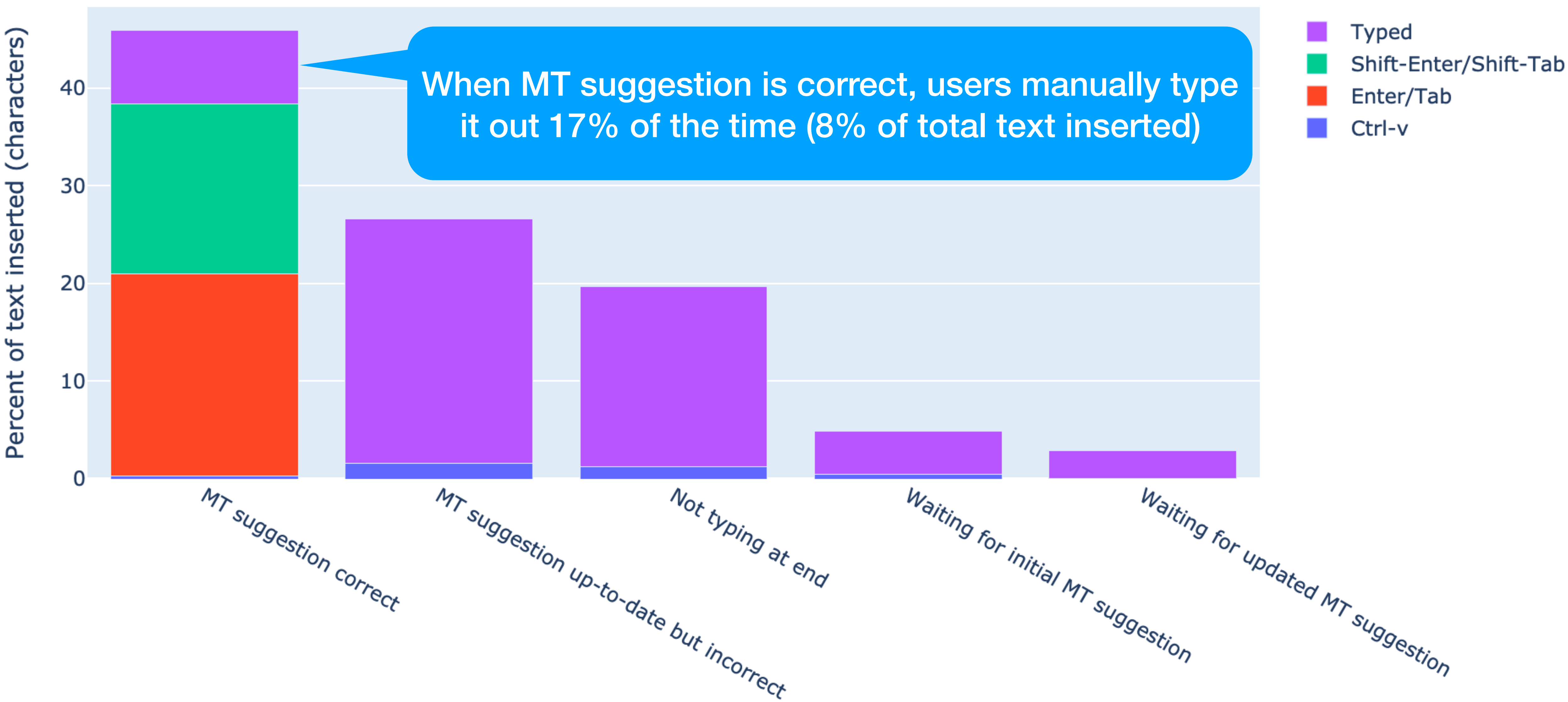
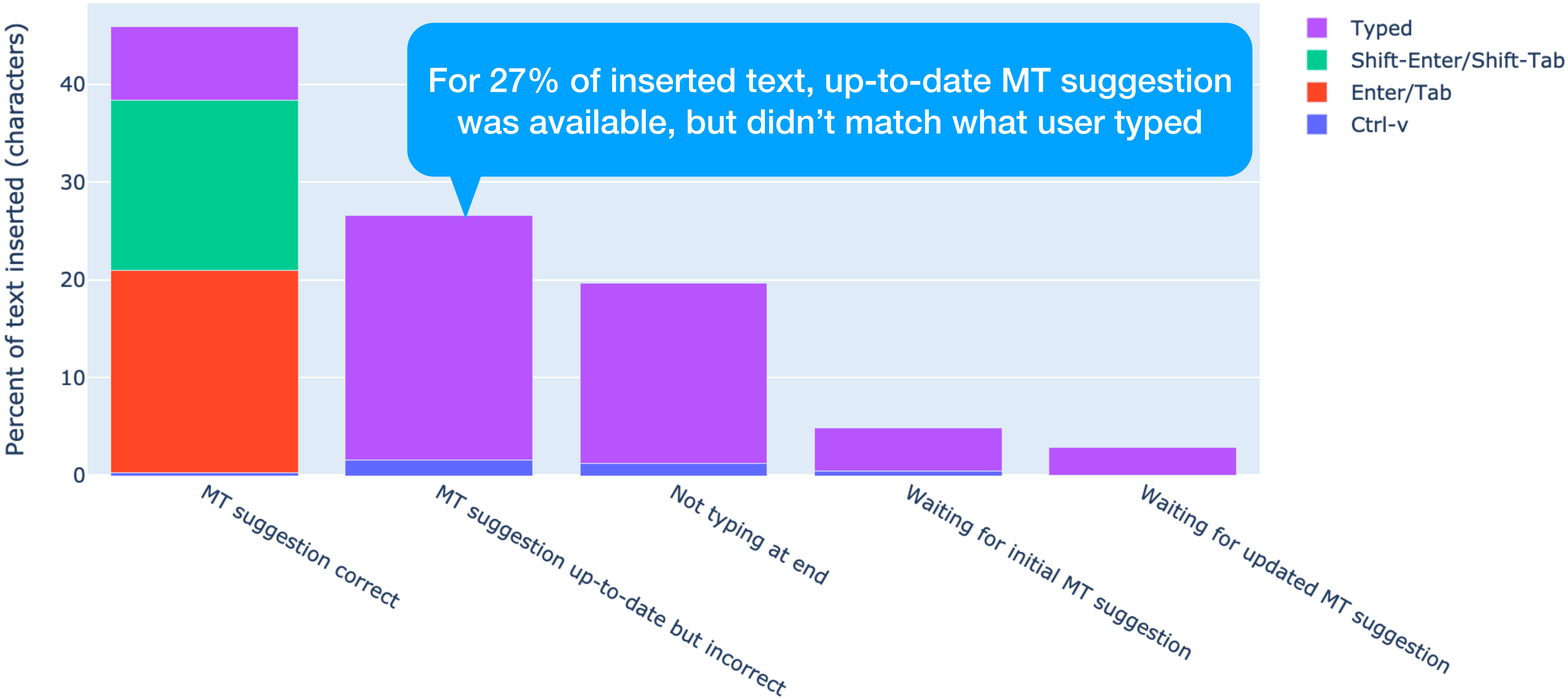


How often are our MT suggestions available and correct?



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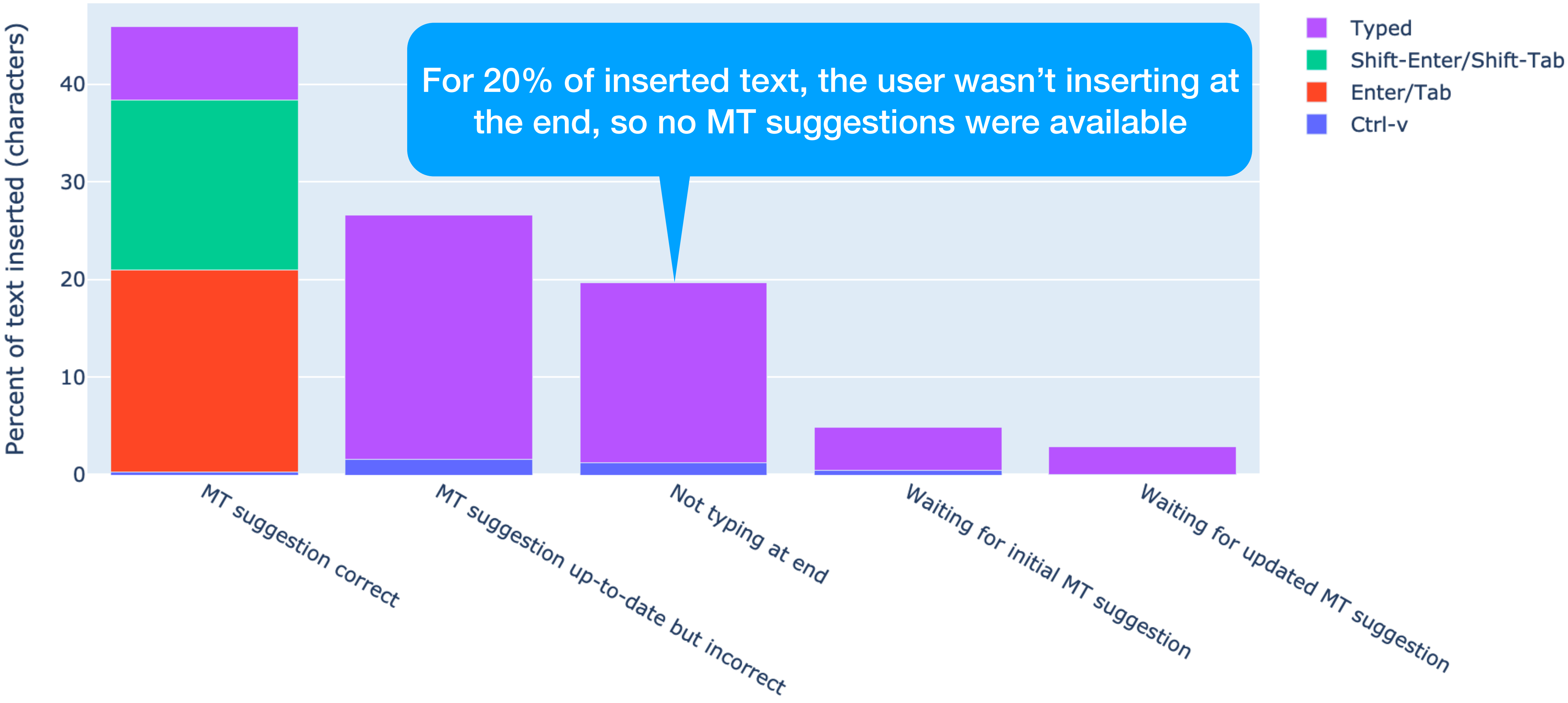

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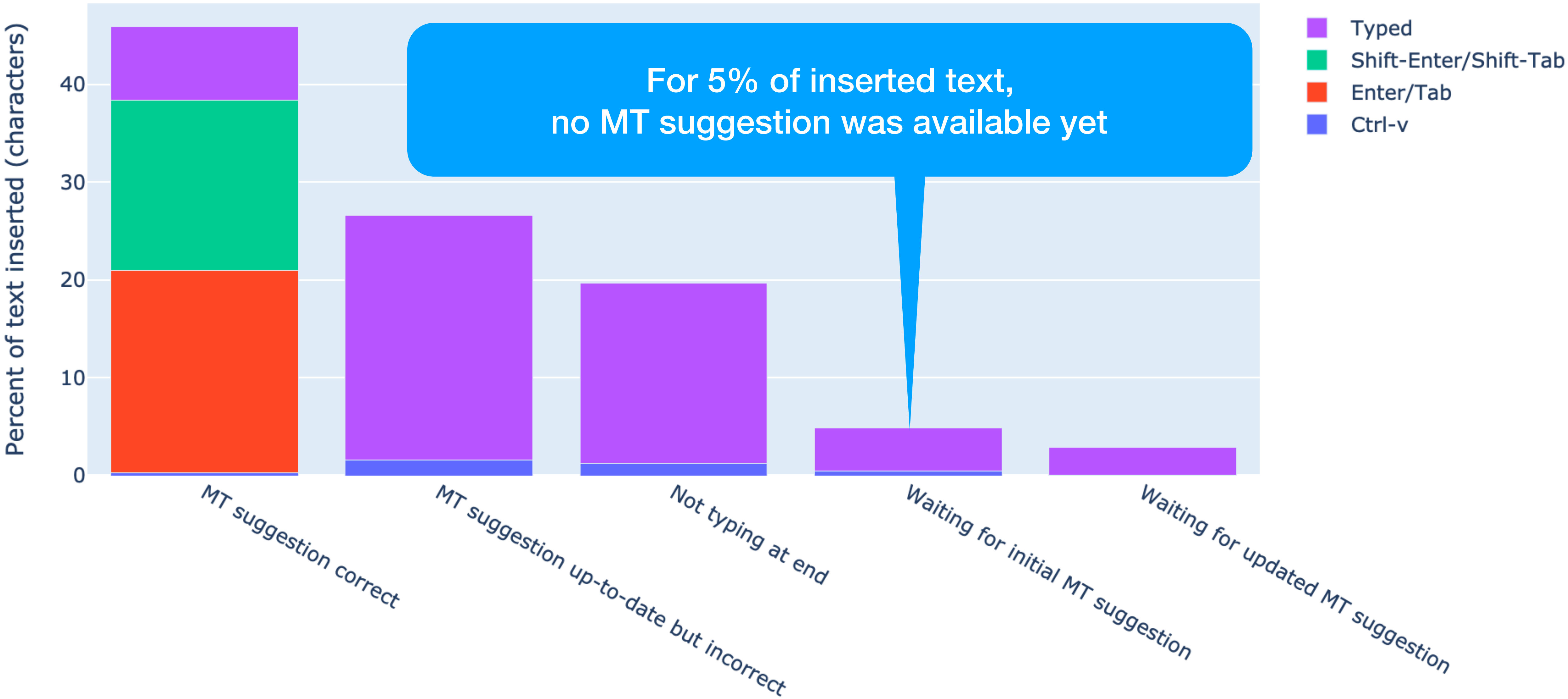
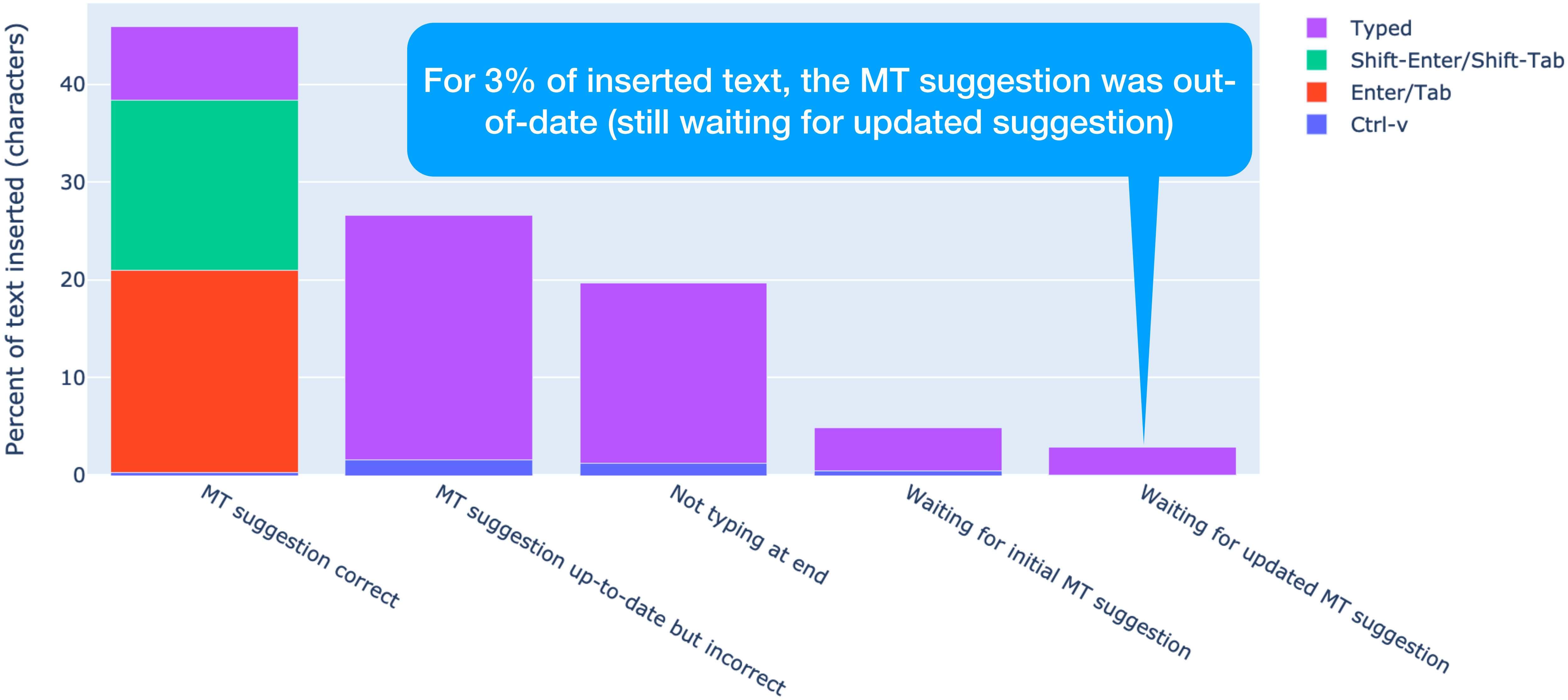


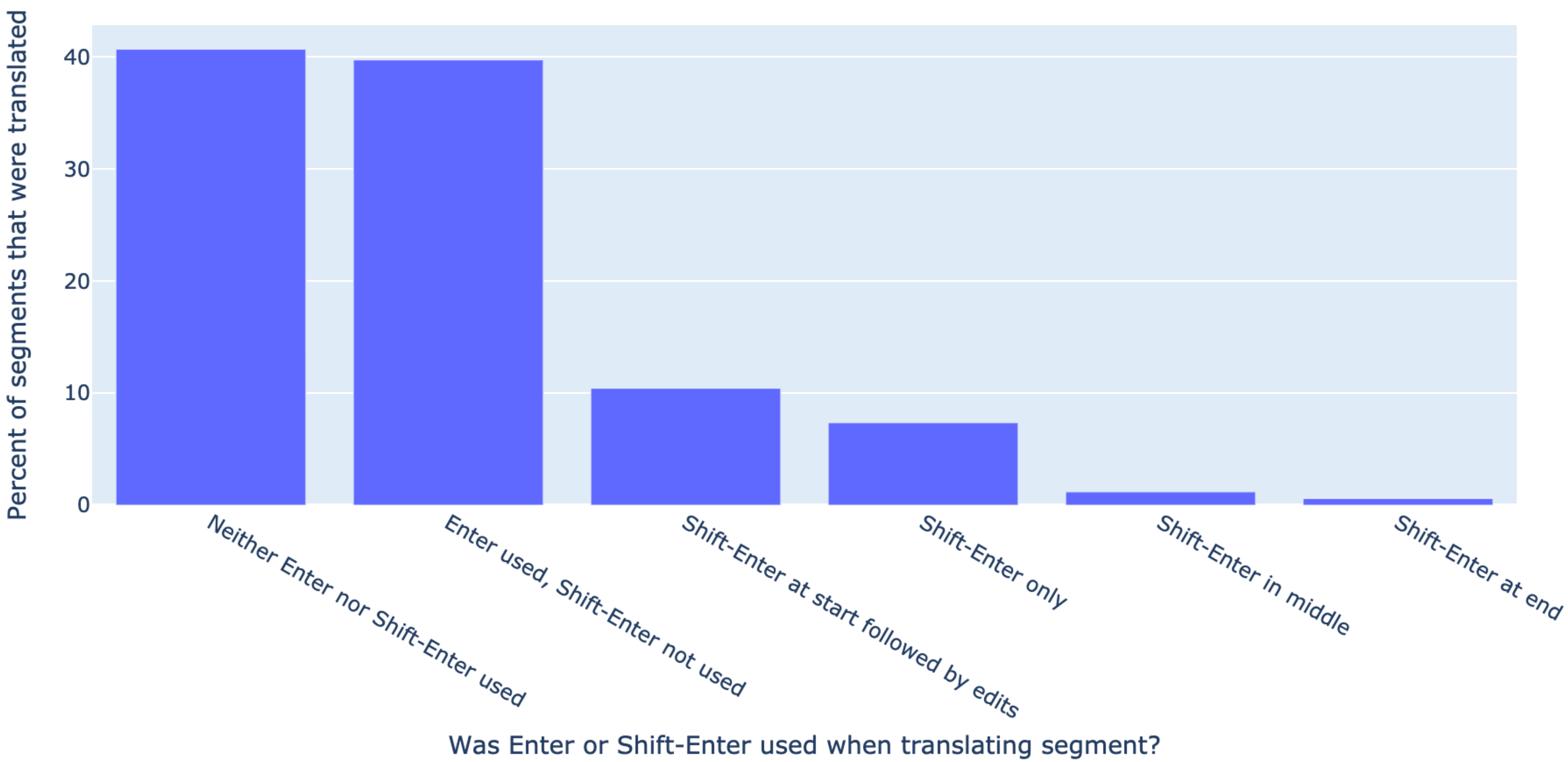
How often are our MT suggestions available and correct?



Are users using Lilt interactively, or as a post-editing system?

- We see a lot of users are using Shift-Enter (accept the entire remaining MT suggestion)
- We also see a lot of users making insertions outside the end of the segment
- Are more users using Lilt in an interactive, suffix-suggestion style, or post-editing?

Are users using Lilt interactively, or as a post-editing system?



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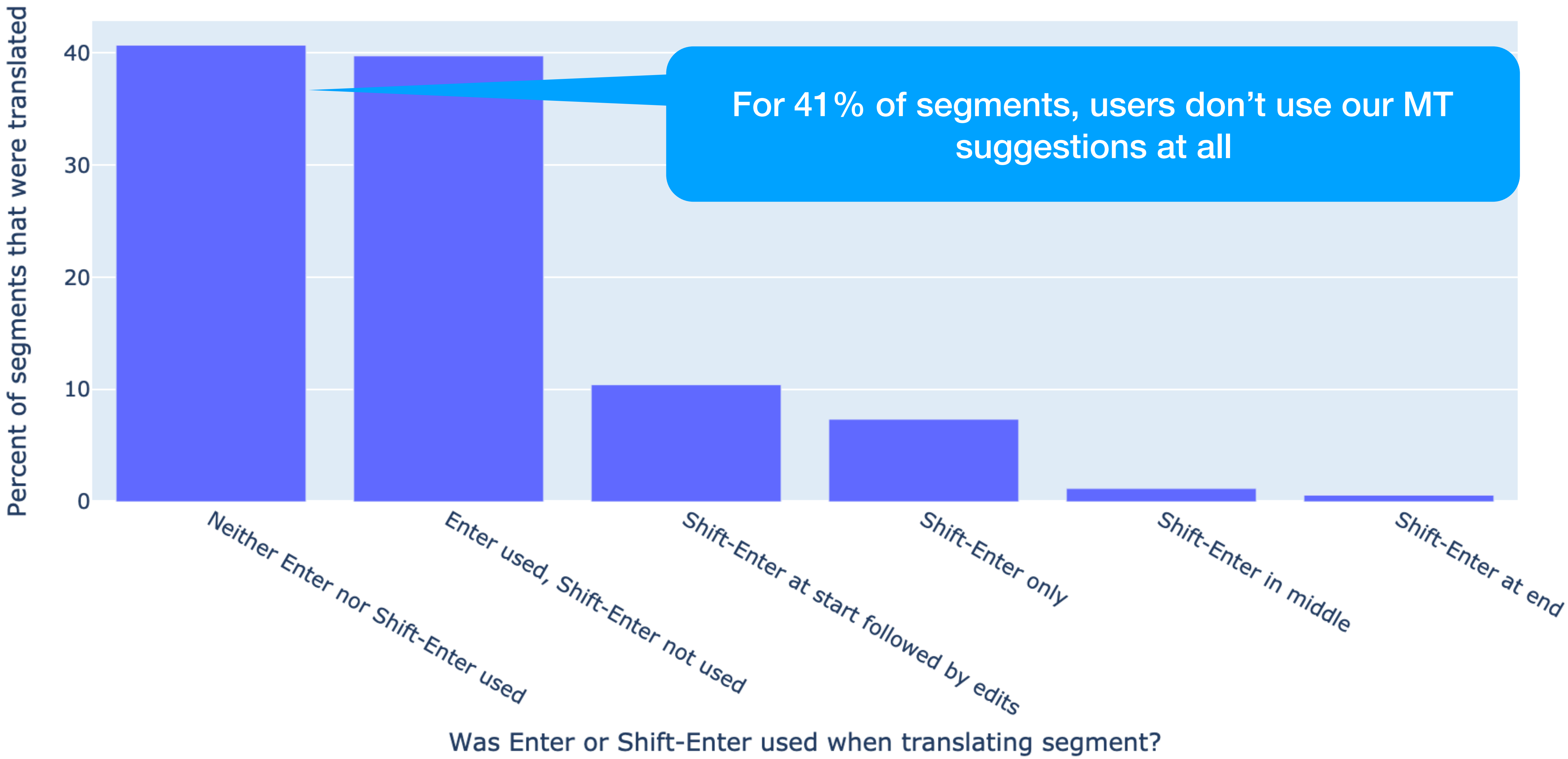

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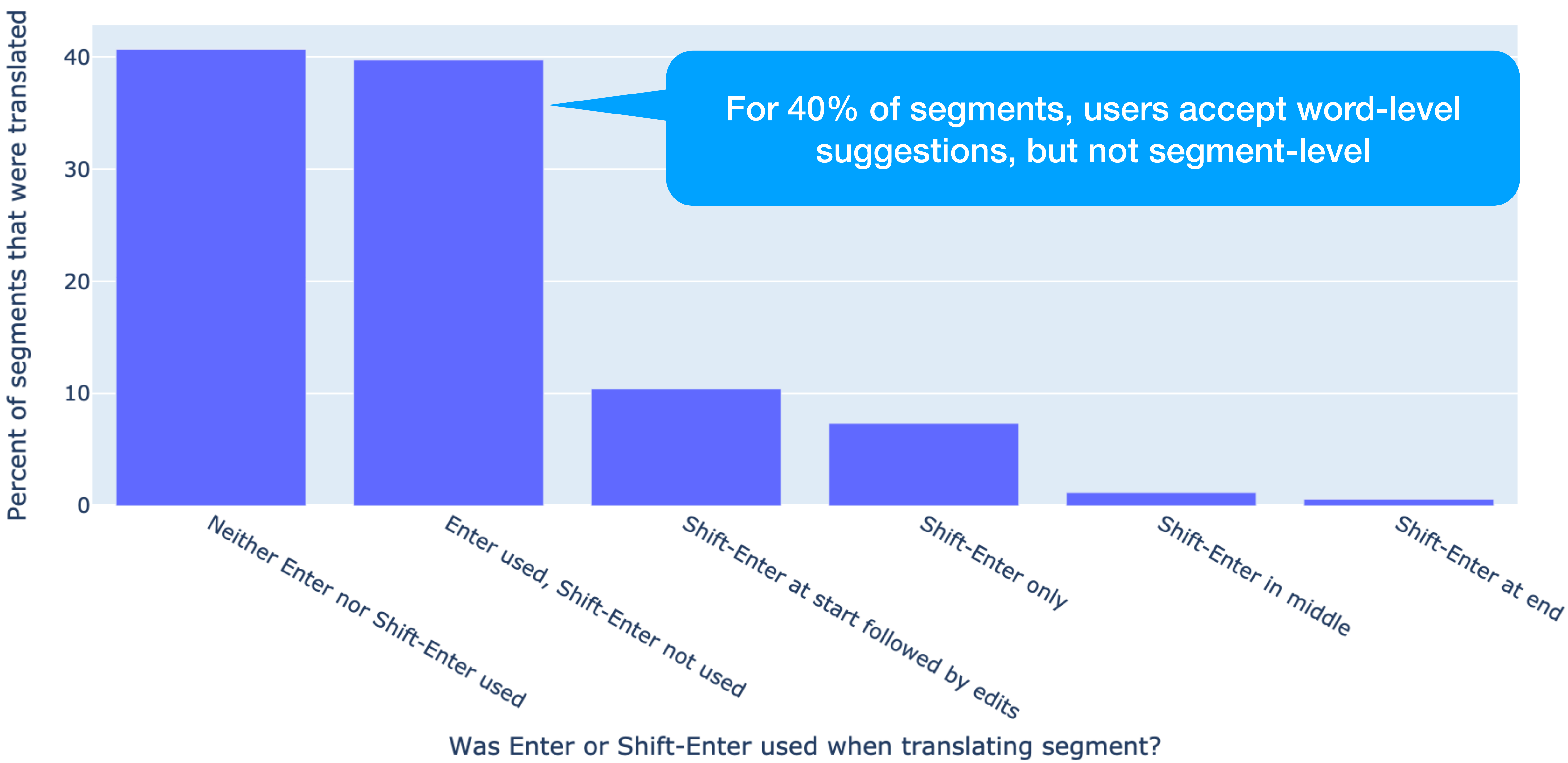
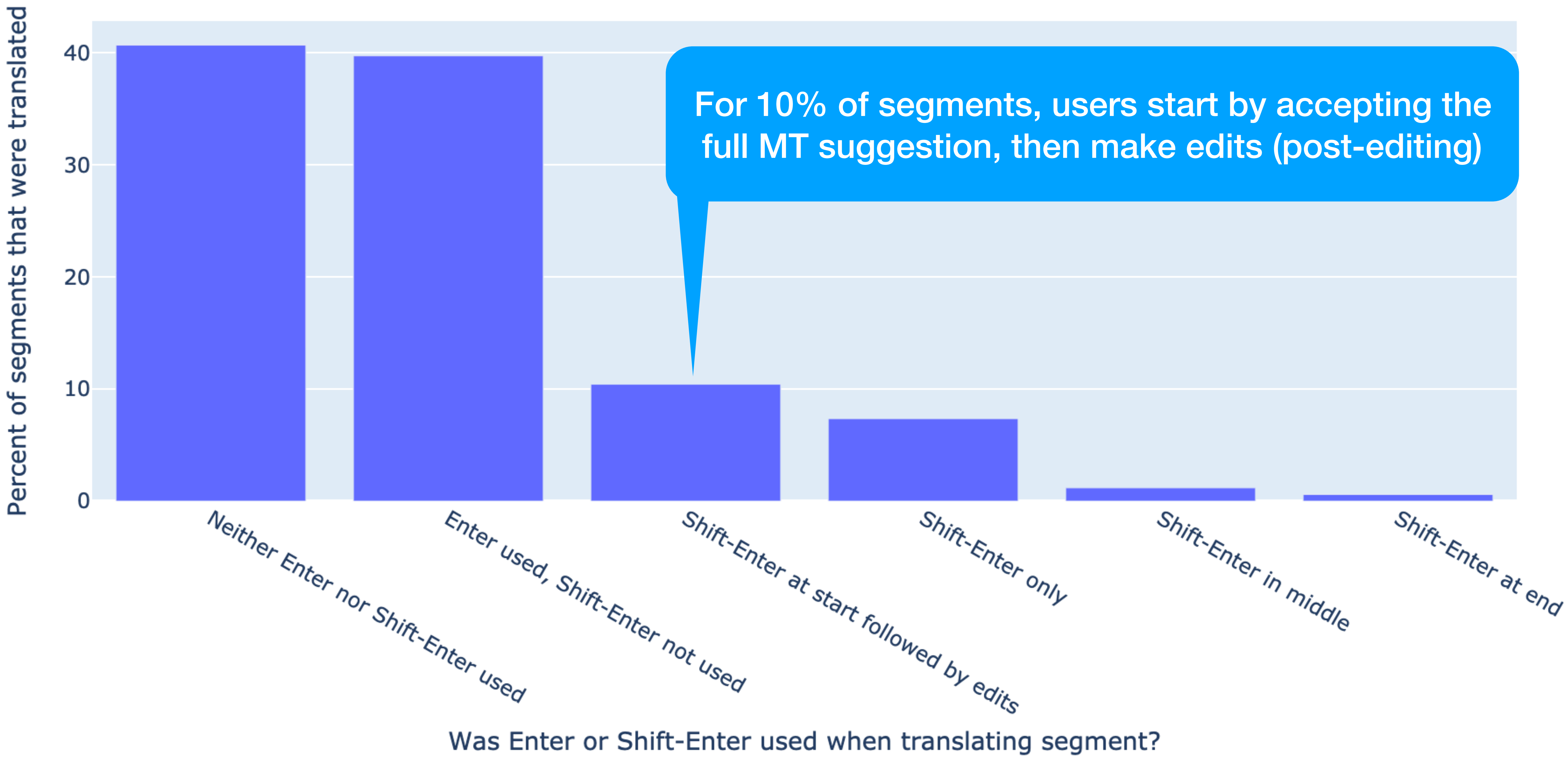
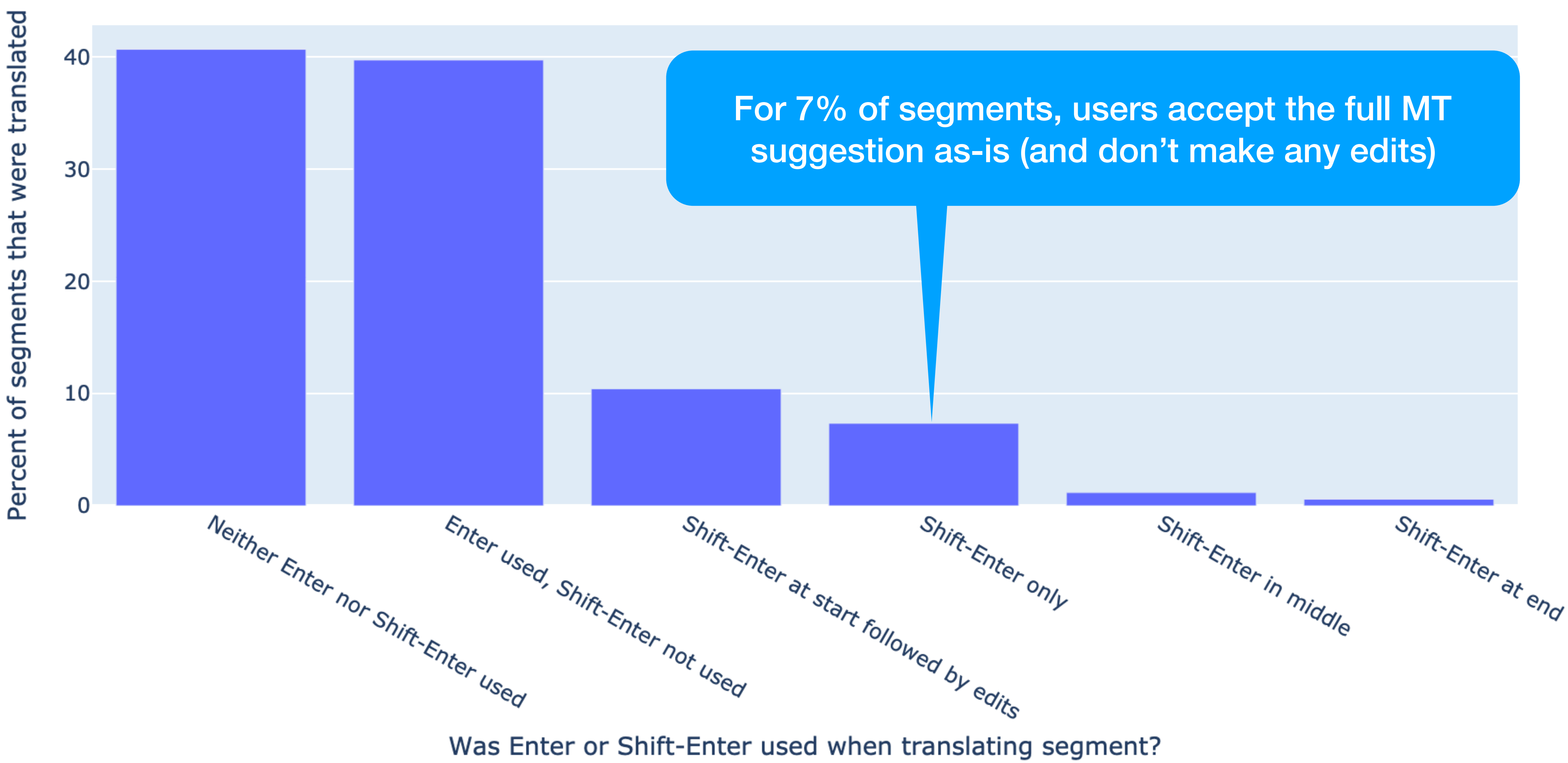


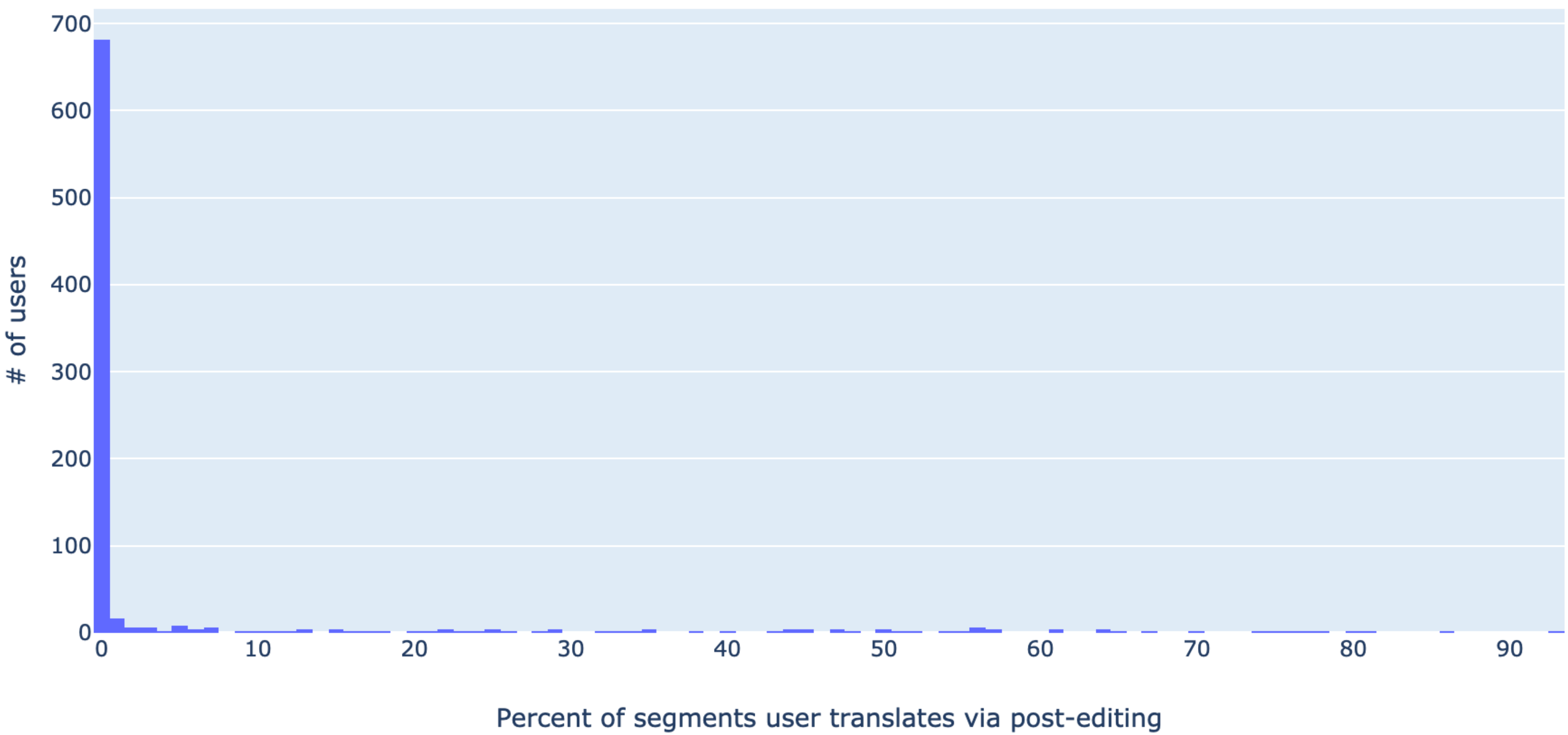
Are users using Lilt interactively, or as a post-editing system?



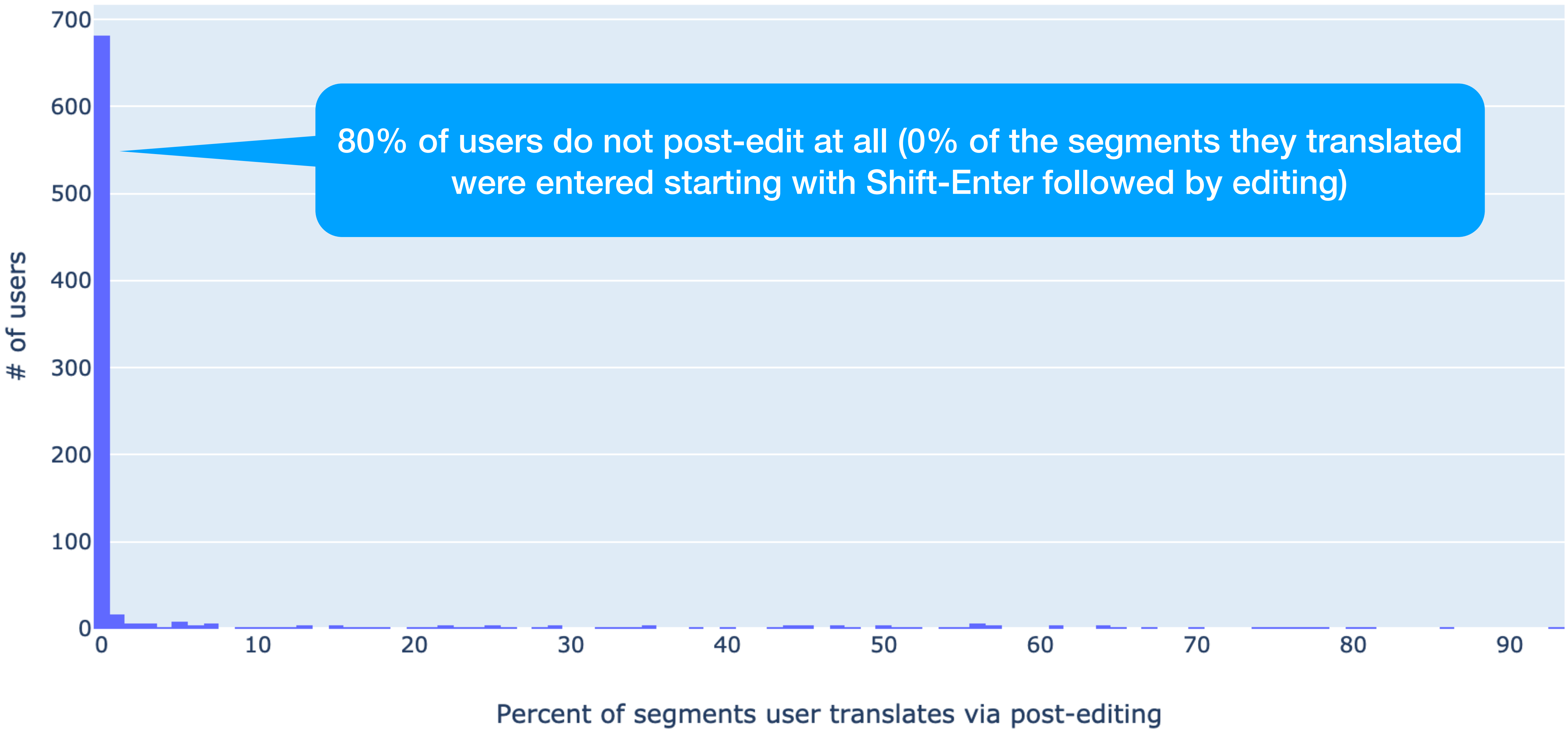
Are users using Lilt interactively, or as a post-editing system?



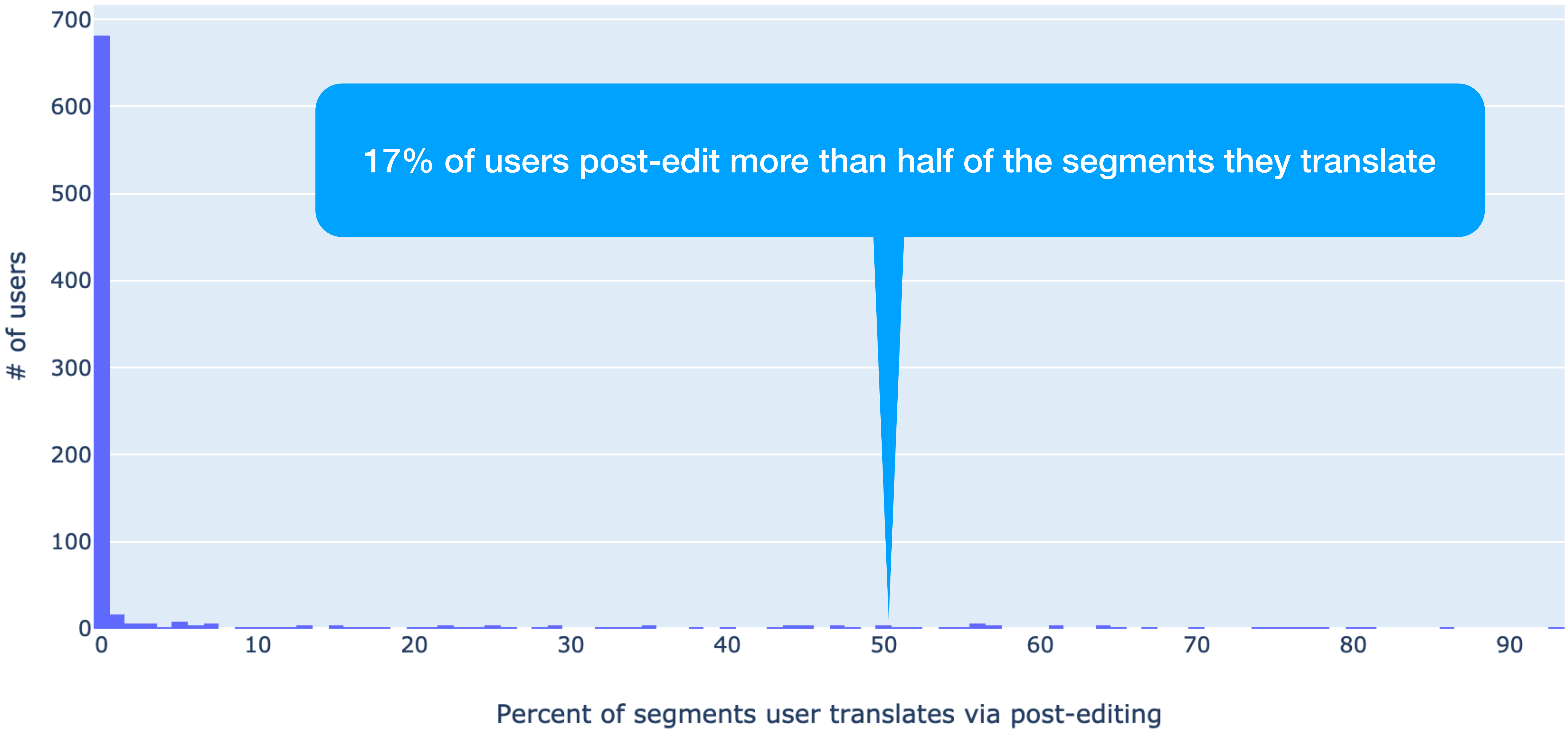
Histogram of users by percent of segments they post-edit



Histogram of users by percent of segments they post-edit



Histogram of users by percent of segments they post-edit

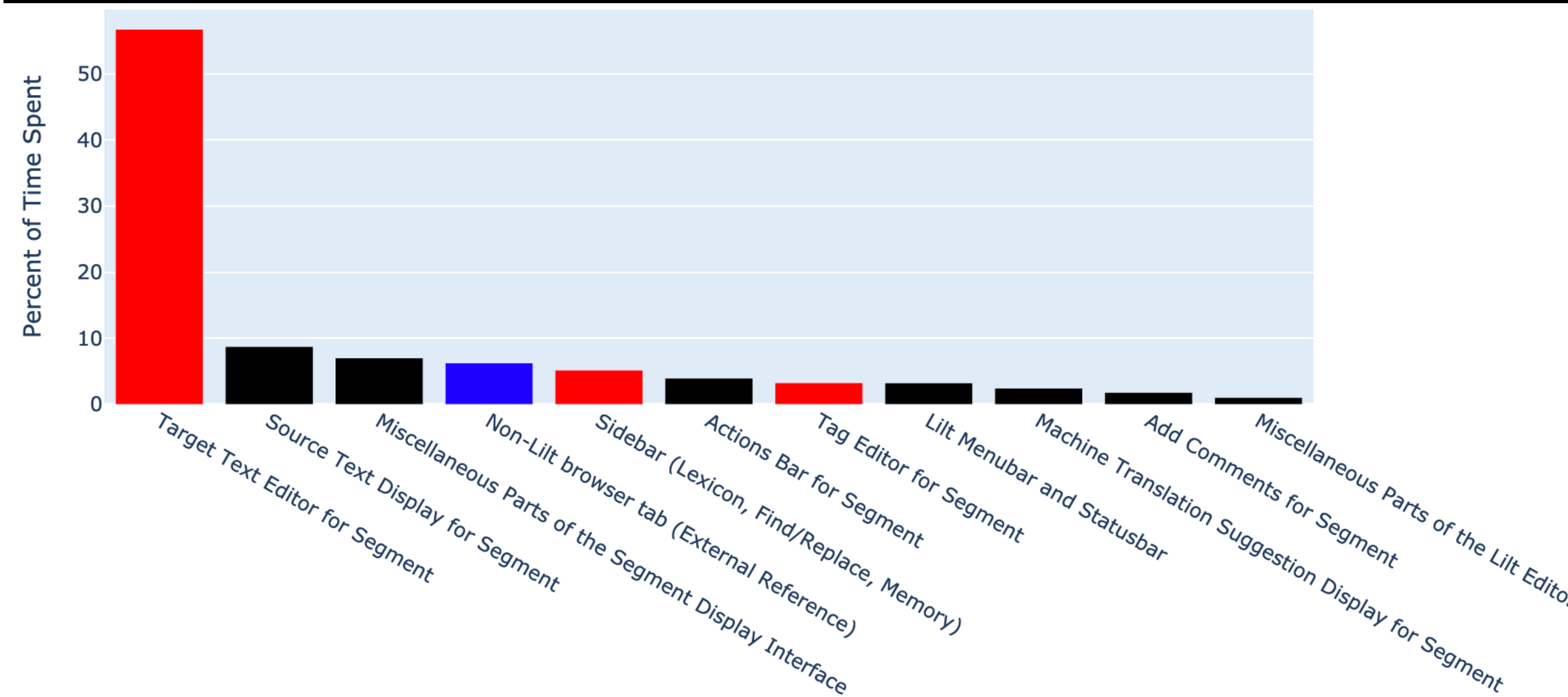


How do translators spend their time on Lilt?

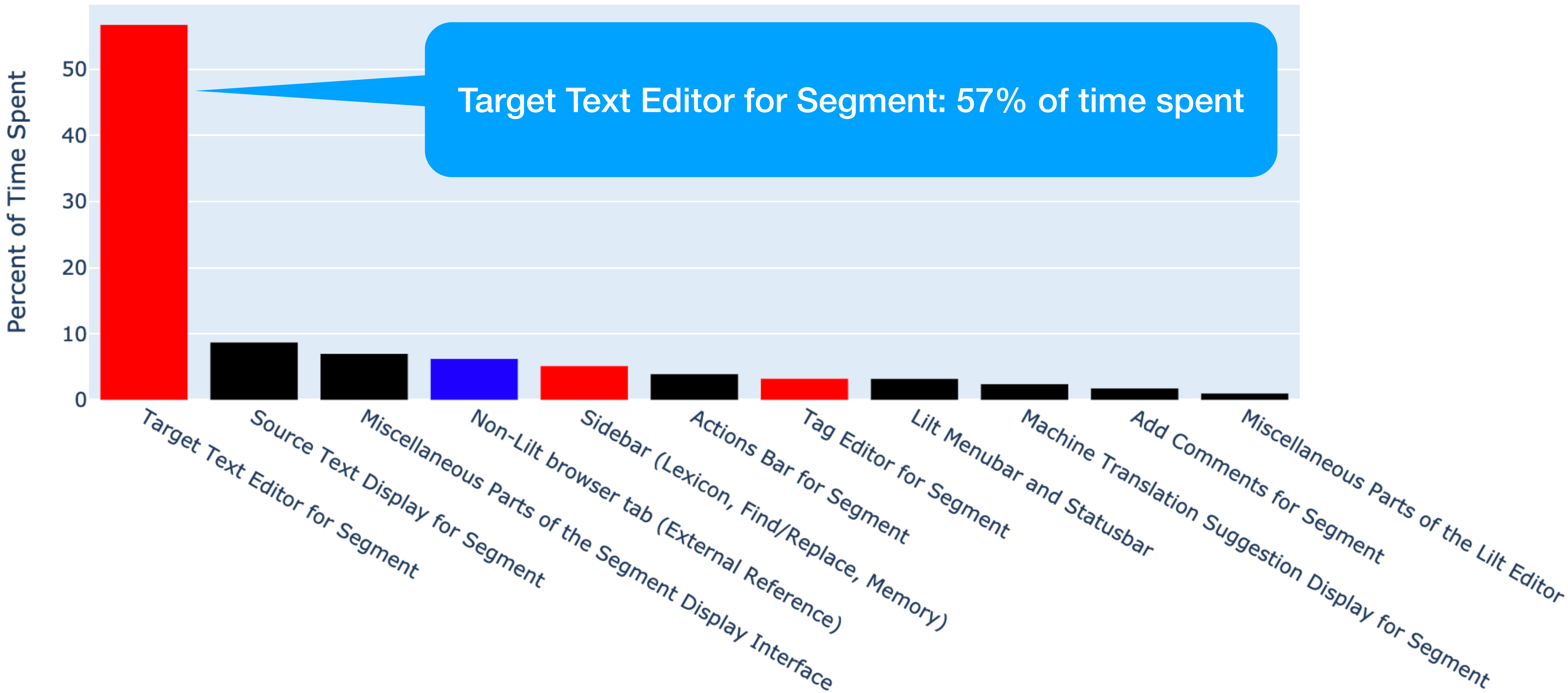
Our efforts have focused on helping translators type translations faster via interactive MT. Is that actually most time-consuming part?

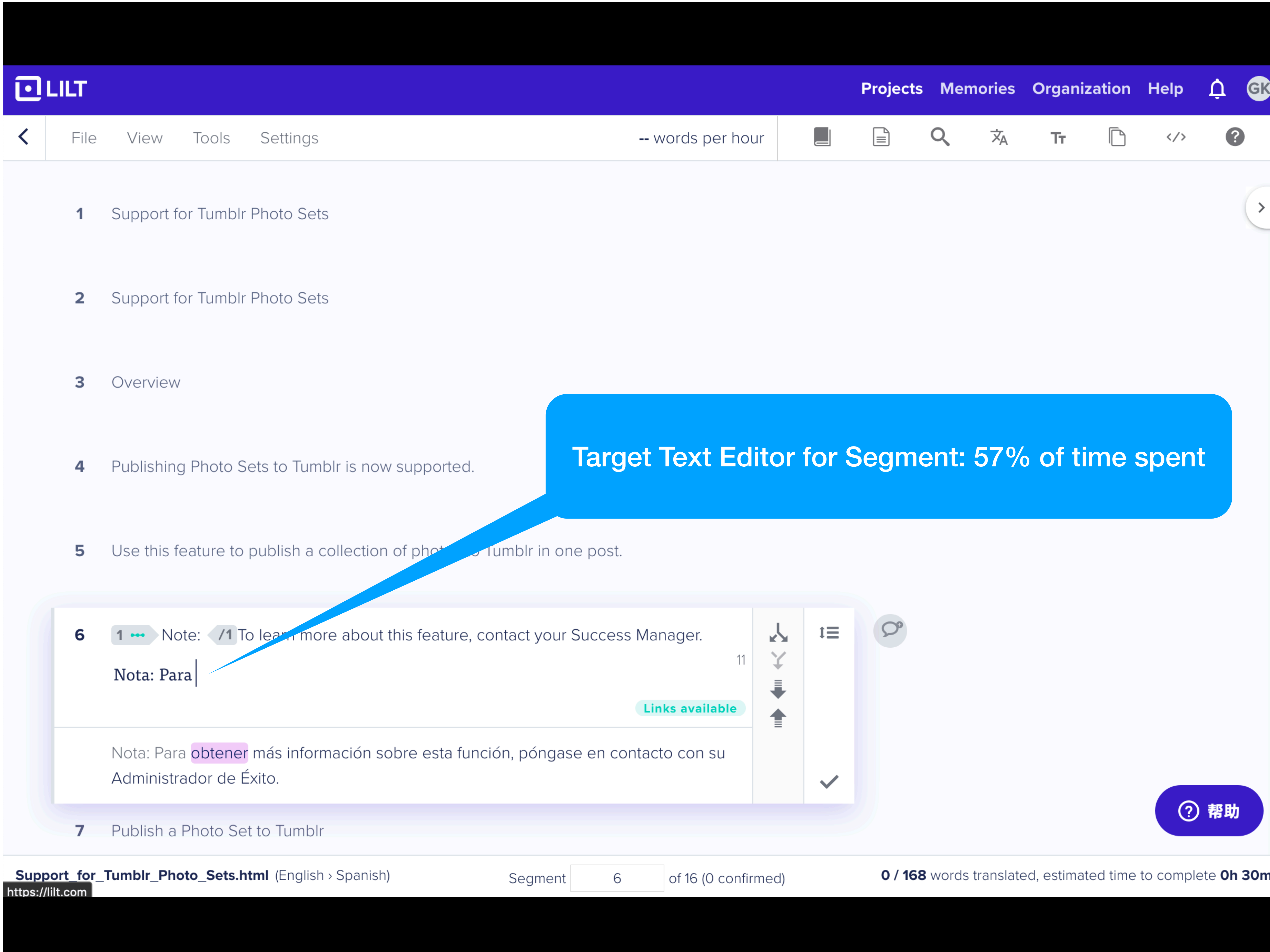
Data based on mouse and keyboard activity while using Lilt in translation mode, permitting up to 30 seconds of idle time between events

How do translators spend their time on Lilt?

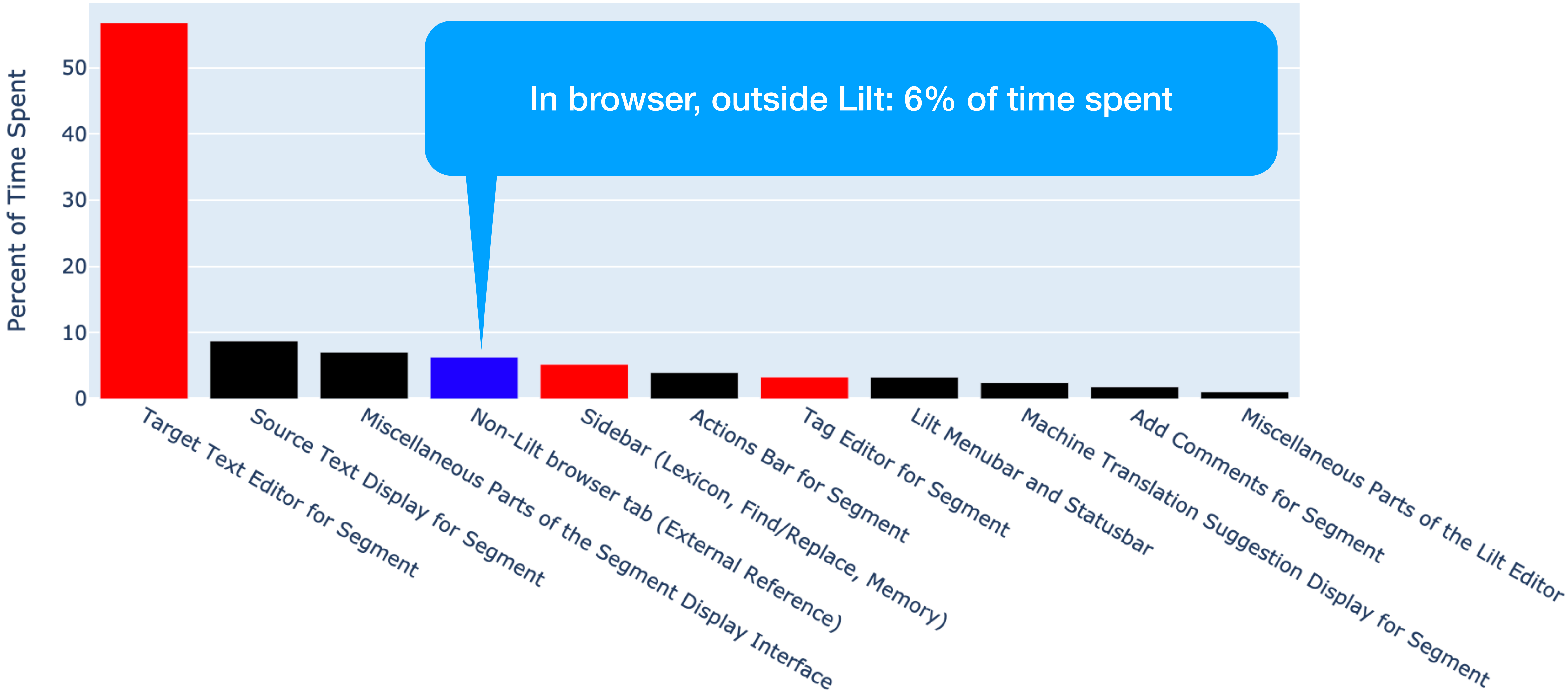


How do translators spend their time on Lilt?

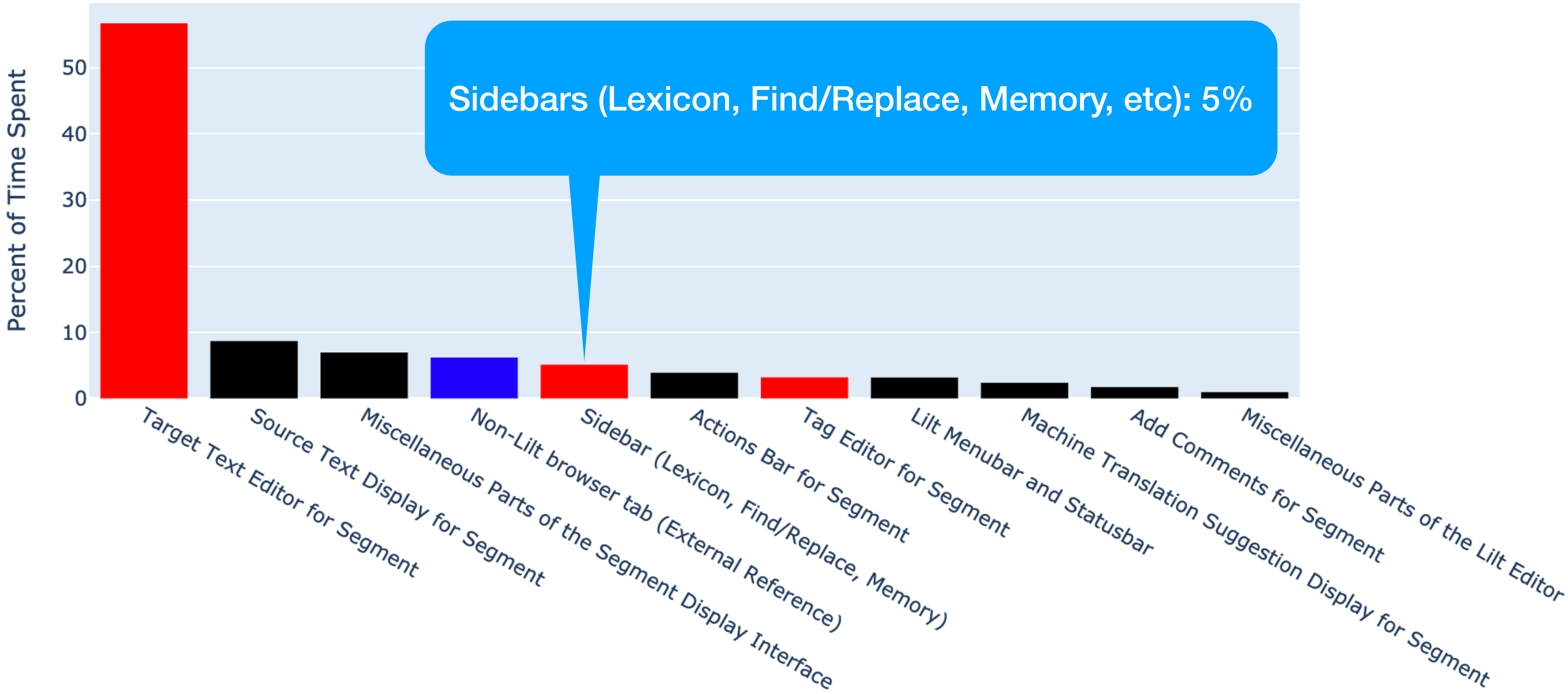


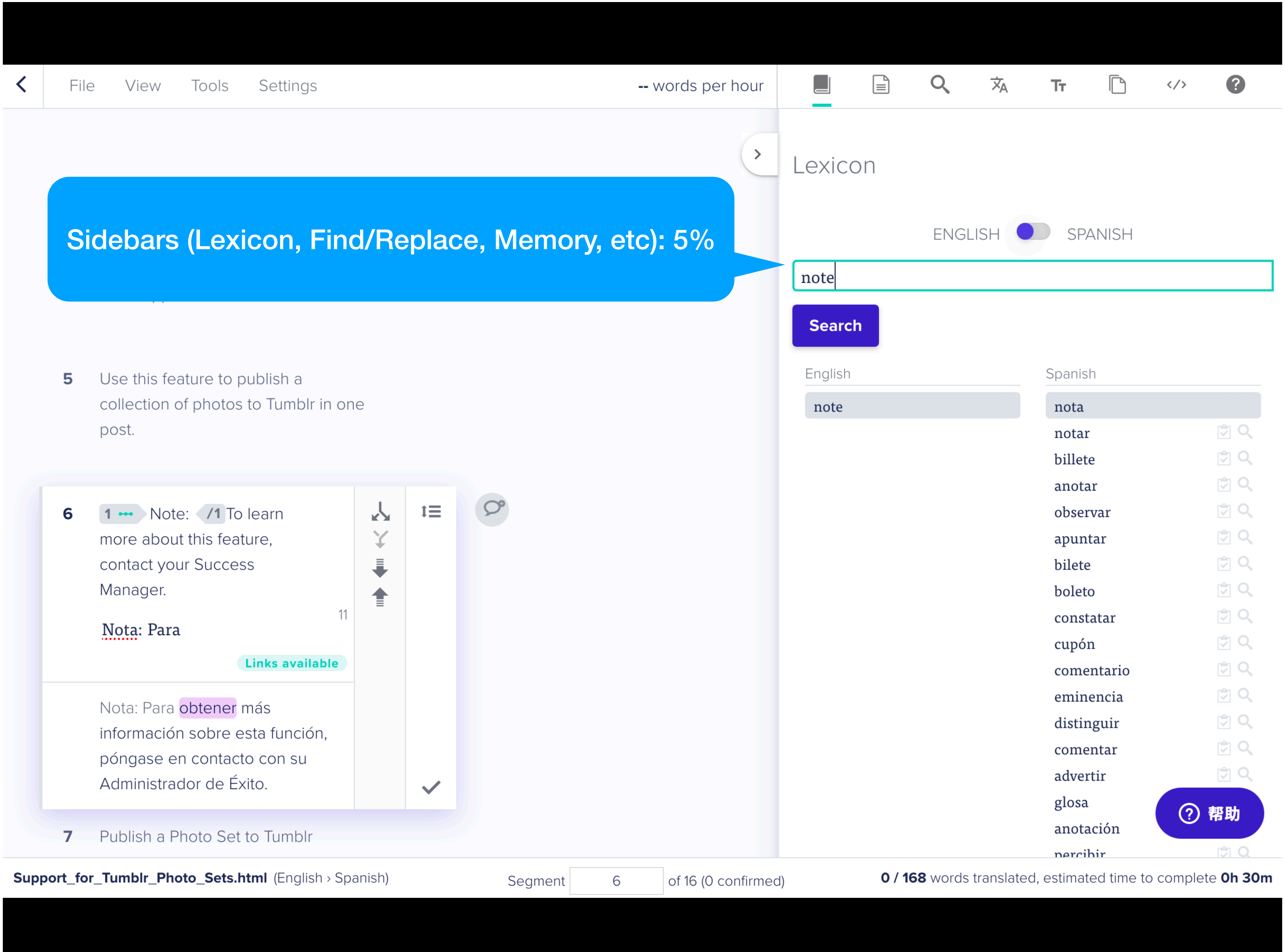

LILT
Projects
Memories
Organization
Help
GK
File
View
Tools
Settings
-- words per hour
1 Support for Tumblr Photo Sets
2 Support for Tumblr Photo Sets
3 Overview
4 Publishing Photo Sets to Tumblr is now supported.
5 Use this feature to publish a collection of photos to Tumblr in one post.
Target Text Editor for Segment: 57% of time spent
6 1 Note: /1 To learn more about this feature, contact your Success Manager.
Nota: Para
11
Links available
Nota: Para obtener más información sobre esta función, póngase en contacto con su Administrador de Éxito.
7 Publish a Photo Set to Tumblr
帮助
Support_for_Tumblr_Photo_Sets.html (English › Spanish)
Segment 6 of 16 (0 confirmed)
0 / 168 words translated, estimated time to complete 0h 30m
https://lilt.com

How do translators spend their time on Lilt?

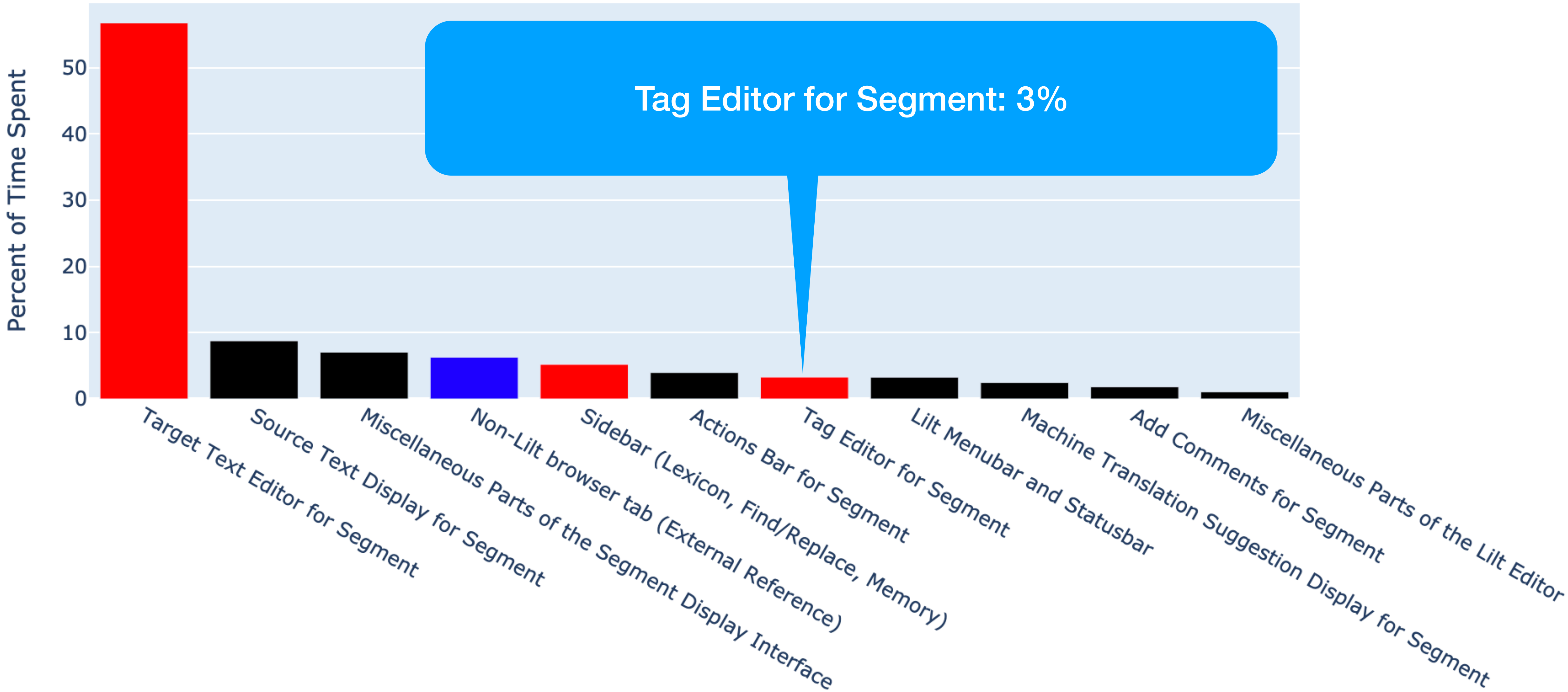


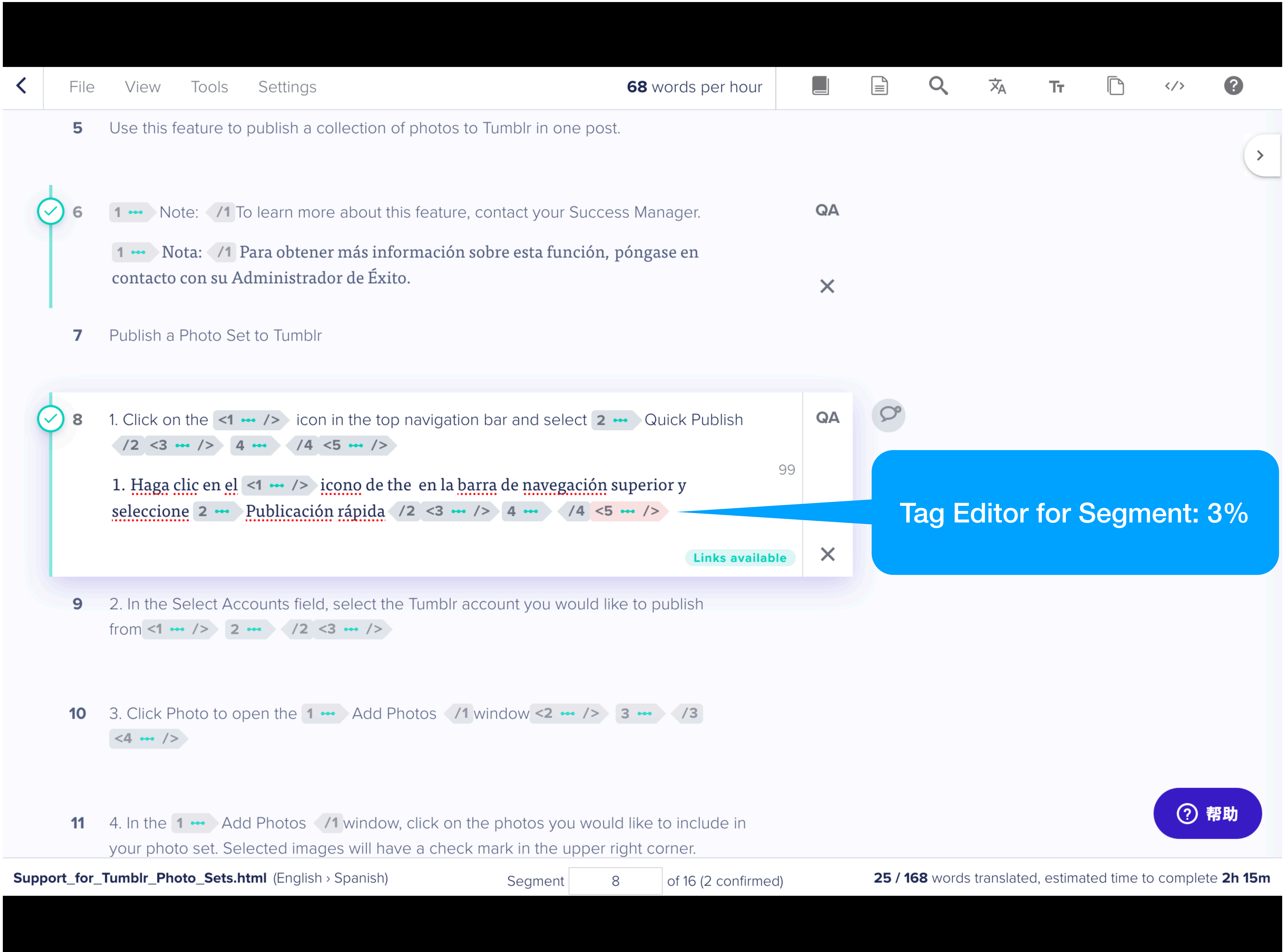
How do translators spend their time on Lilt?



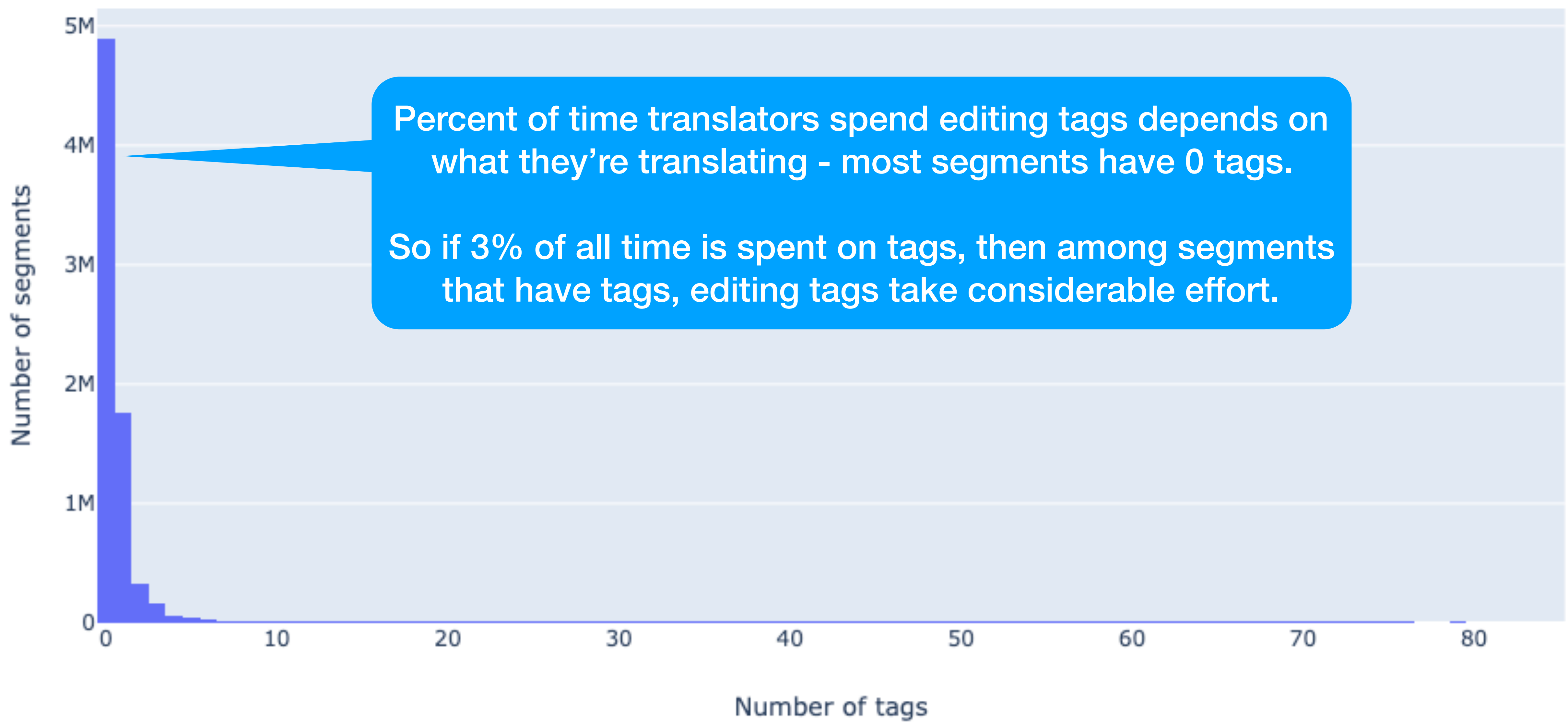

File
View
Tools
Settings
-- words per hour
Lexicon
Sidebars (Lexicon, Find/Replace, Memory, etc): 5%
ENGLISH
SPANISH
note
Search
English
Spanish
note
nota
notar
billete
anotar
observar
apuntar
bilete
boleto
constatar
cupón
comentario
eminencia
distinguir
comentar
advertir
glosa
anotación
5
Use this feature to publish a collection of photos to Tumblr in one post.
6
1
Note:
/1
To learn more about this feature, contact your Success Manager.
11
Nota: Para
Links available
Nota: Para obtener más información sobre esta función, póngase en contacto con su Administrador de Éxito.
7
Publish a Photo Set to Tumblr
帮助
Support_for_Tumblr_Photo_Sets.html (English › Spanish)
Segment
6
of 16 (0 confirmed)
0 / 168 words translated, estimated time to complete 0h 30m

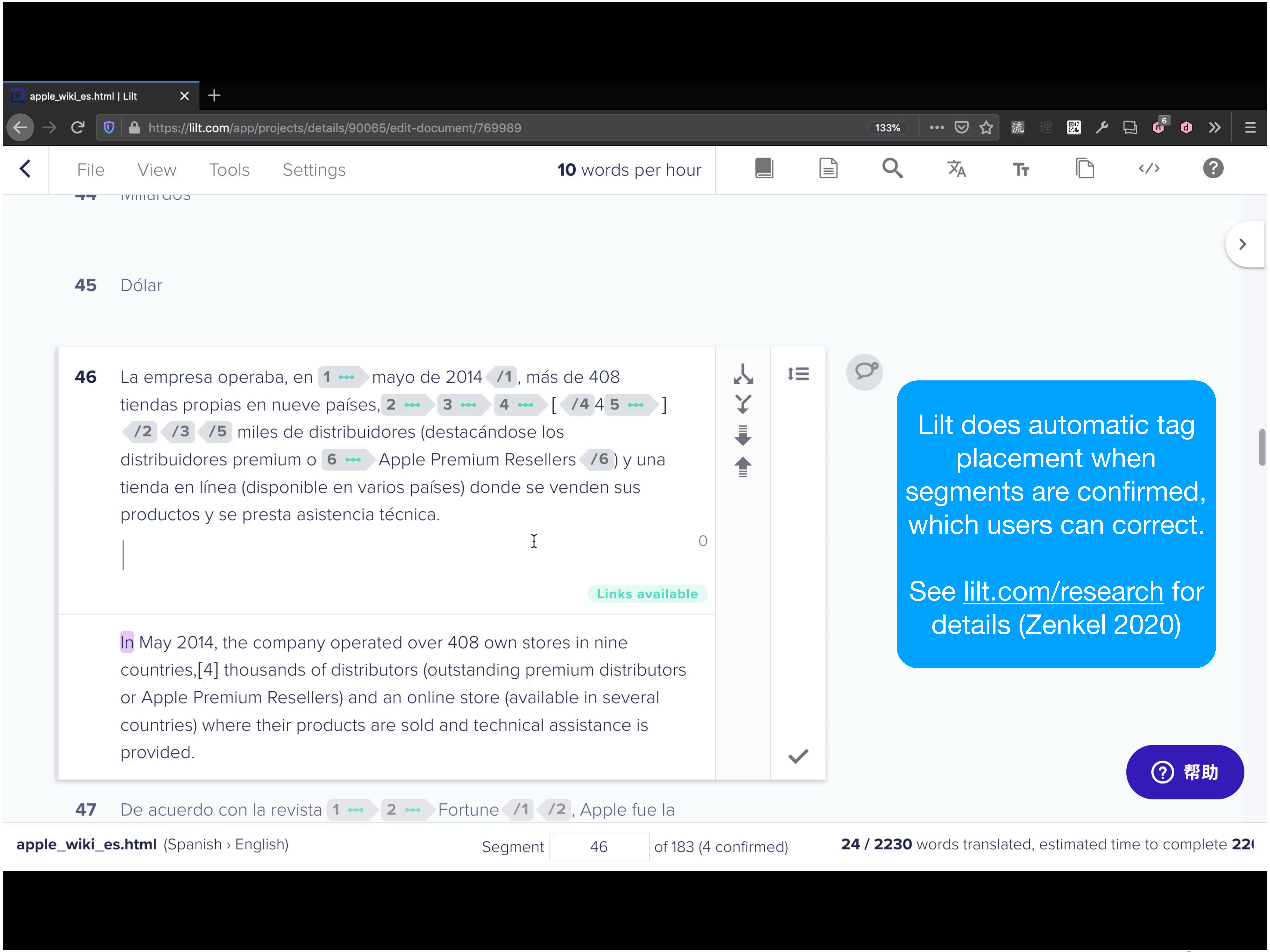
How do translators spend their time on Lilt?



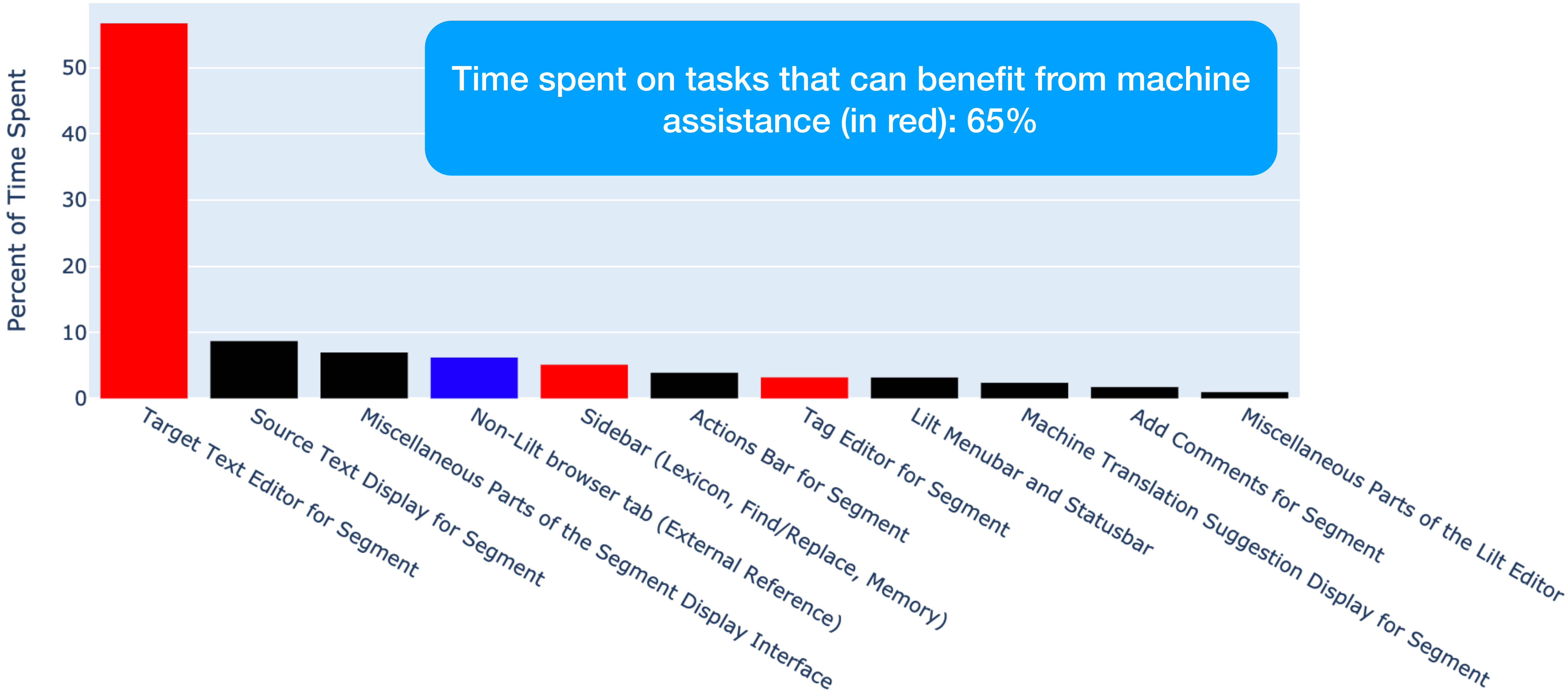

File View Tools Settings
68 words per hour
5 Use this feature to publish a collection of photos to Tumblr in one post.
6 1 Note: /1 To learn more about this feature, contact your Success Manager.
1 Nota: /1 Para obtener más información sobre esta función, póngase en contacto con su Administrador de Éxito.
QA
7 Publish a Photo Set to Tumblr
8 1. Click on the <1 /> icon in the top navigation bar and select 2 Quick Publish /2 <3 /> 4 /4 <5 />
99
1. Haga clic en el <1 /> icono de the en la barra de navegación superior y seleccione 2 Publicación rápida /2 <3 /> 4 /4 <5 />
QA
Links available
Tag Editor for Segment: 3%
9 2. In the Select Accounts field, select the Tumblr account you would like to publish from <1 /> 2 /2 <3 />
10 3. Click Photo to open the 1 Add Photos /1 window <2 /> 3 /3 <4 />
11 4. In the 1 Add Photos /1 window, click on the photos you would like to include in your photo set. Selected images will have a check mark in the upper right corner.
帮助
Support_for_Tumblr_Photo_Sets.html (English › Spanish)
Segment 8 of 16 (2 confirmed)
25 / 168 words translated, estimated time to complete 2h 15m

Histogram of segments by the number of tags

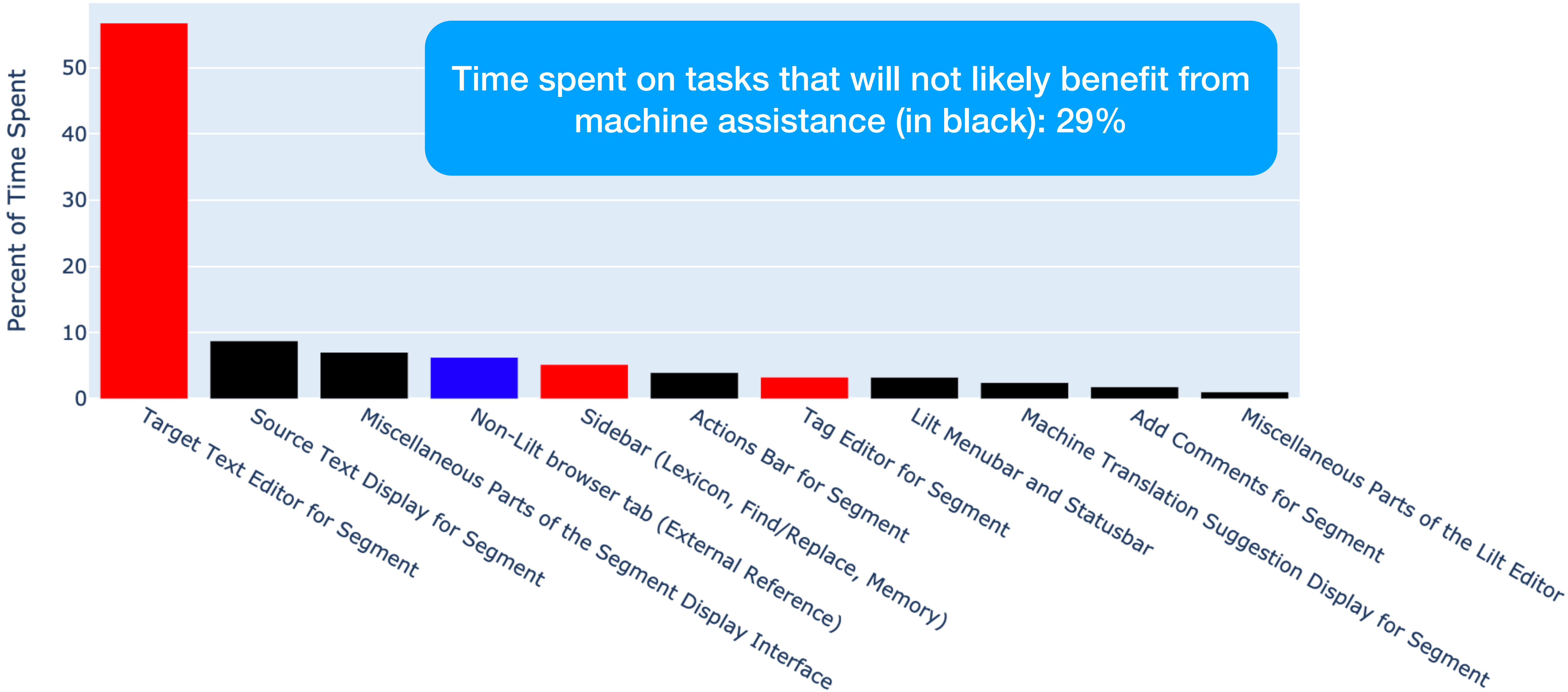



apple_wiki_es.html | Lilt
https://lilt.com/app/projects/details/90065/edit-document/769989
133%
File
View
Tools
Settings
10 words per hour
45 Dólar
46 La empresa operaba, en 1 mayo de 2014 /1, más de 408 tiendas propias en nueve países, 2 3 4 [/4 4 5] /2 /3 /5 miles de distribuidores (destacándose los distribuidores premium o 6 Apple Premium Resellers /6) y una tienda en línea (disponible en varios países) donde se venden sus productos y se presta asistencia técnica.
0
Links available
In May 2014, the company operated over 408 own stores in nine countries,[4] thousands of distributors (outstanding premium distributors or Apple Premium Resellers) and an online store (available in several countries) where their products are sold and technical assistance is provided.
47 De acuerdo con la revista 1 2 Fortune /1 /2, Apple fue la
Lilt does automatic tag placement when segments are confirmed, which users can correct.
See lilt.com/research for details (Zenkel 2020)
帮助
apple_wiki_es.html (Spanish › English)
Segment 46 of 183 (4 confirmed)
24 / 2230 words translated, estimated time to complete 22

How do translators spend their time on Lilt?



How do translators spend their time on Lilt?



Conclusion: A Study of Interactive Machine Translation Use on Lilt

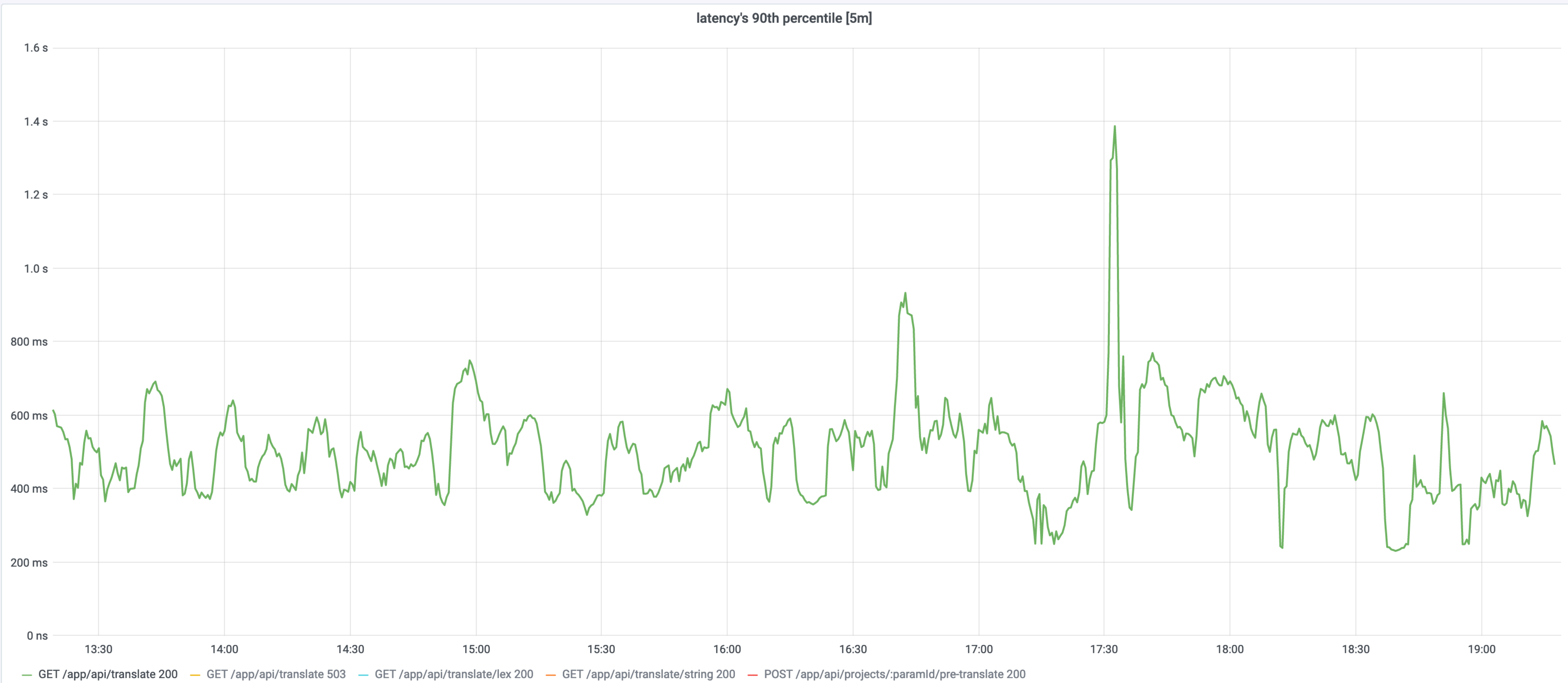
- 57% of translator time is spent on actually writing the translation, which we can optimize with interactive MT.

- Our prefix-constrained interactive MT shows the correct suggestion to translators for 46% of the text they type. Of this, they use our autocompletion for 83% of the text.

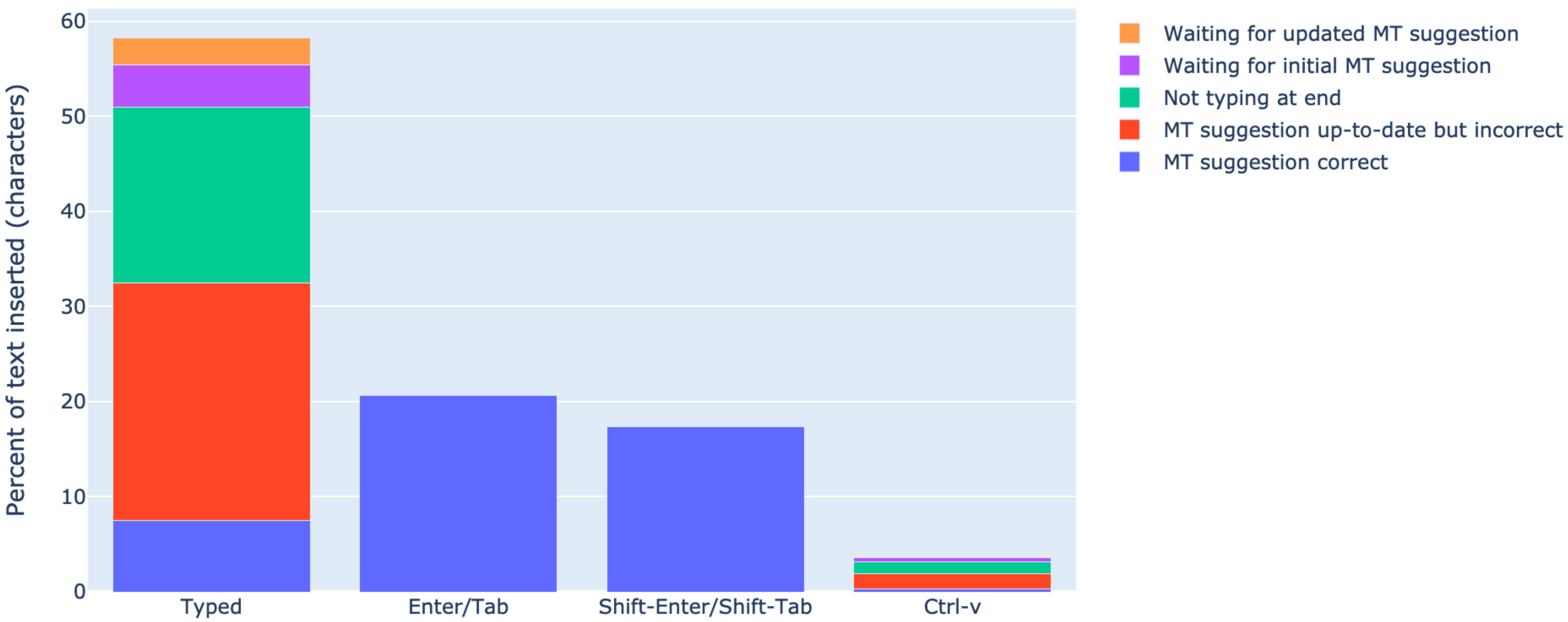
- Main areas for improvement are MT quality and showing suggestions when user isn't typing at the end. Latency is very good (< 500ms).

- While Lilt is used in an interactive style 4x more than post-editing, 17% of our users primarily use it for post-editing.

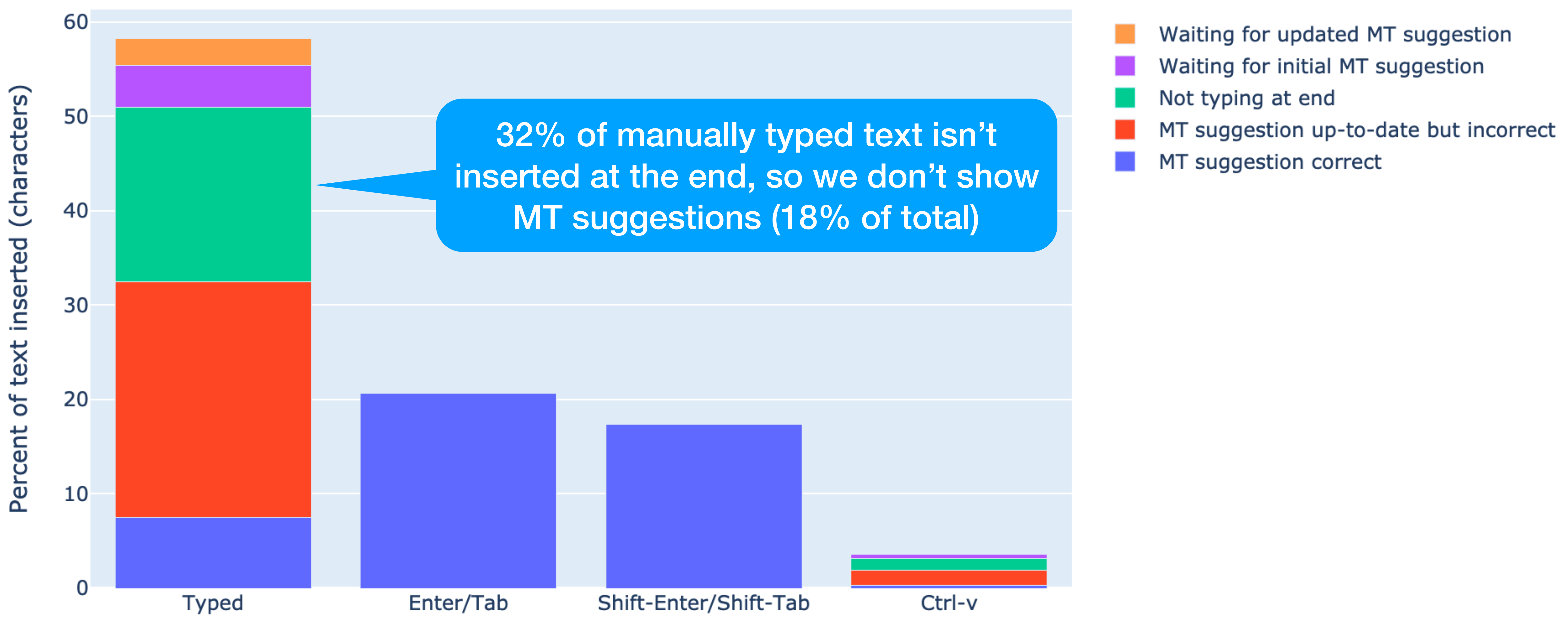
Backup slides


latency's 90th percentile [5m]
1.6 s
1.4 s
1.2 s
1.0 s
800 ms
600 ms
400 ms
200 ms
0 ns
13:30
14:00
14:30
15:00
15:30
16:00
16:30
17:00
17:30
18:00
18:30
19:00
GET /app/api/translate 200
GET /app/api/translate 503
GET /app/api/translate/lex 200
GET /app/api/translate/string 200
POST /app/api/projects/:paramId/pre-translate 200

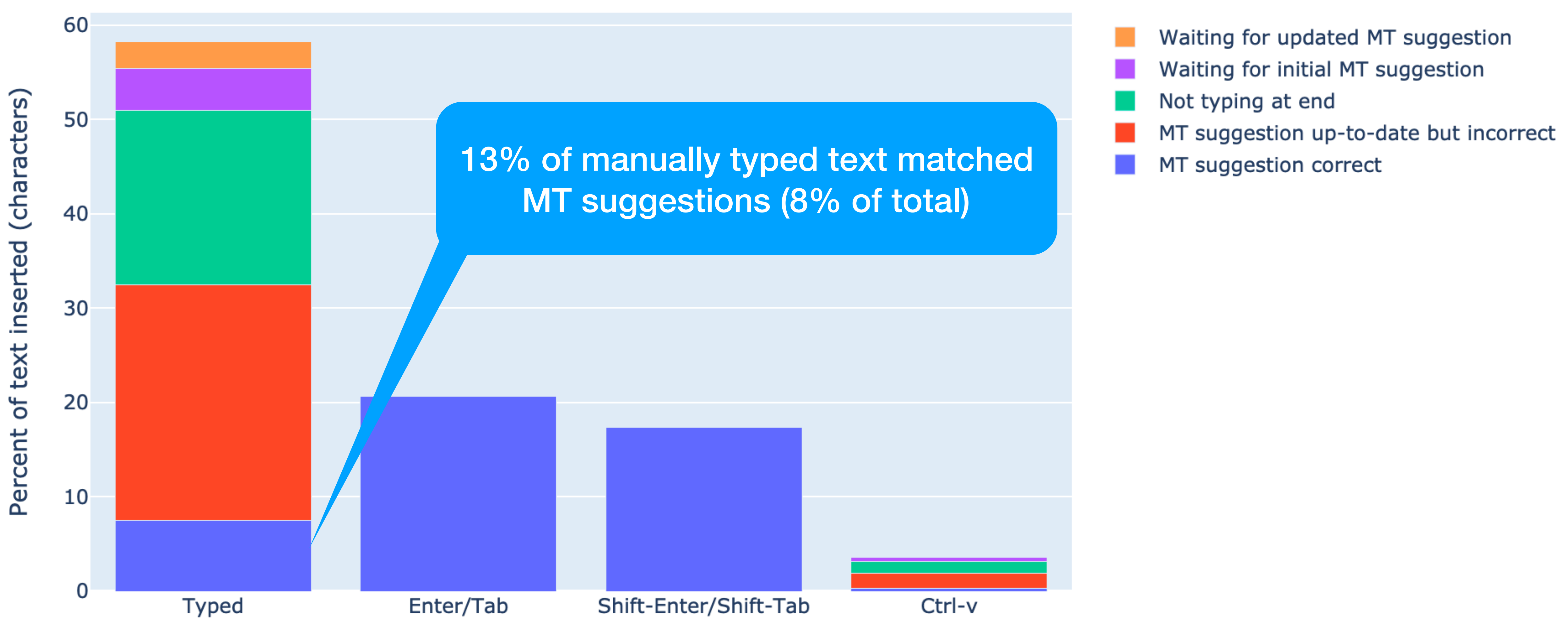
Keys through which text is inserted, broken down by MT state



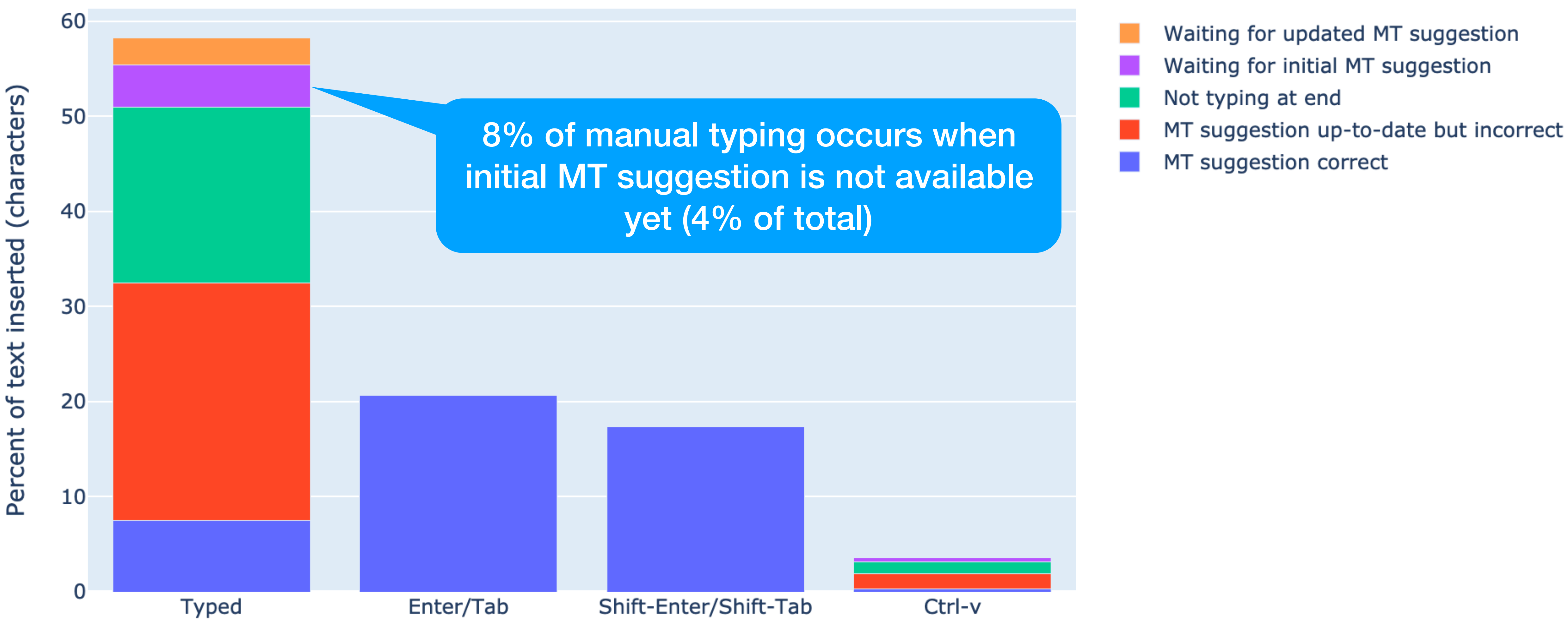
Keys through which text is inserted, broken down by MT state



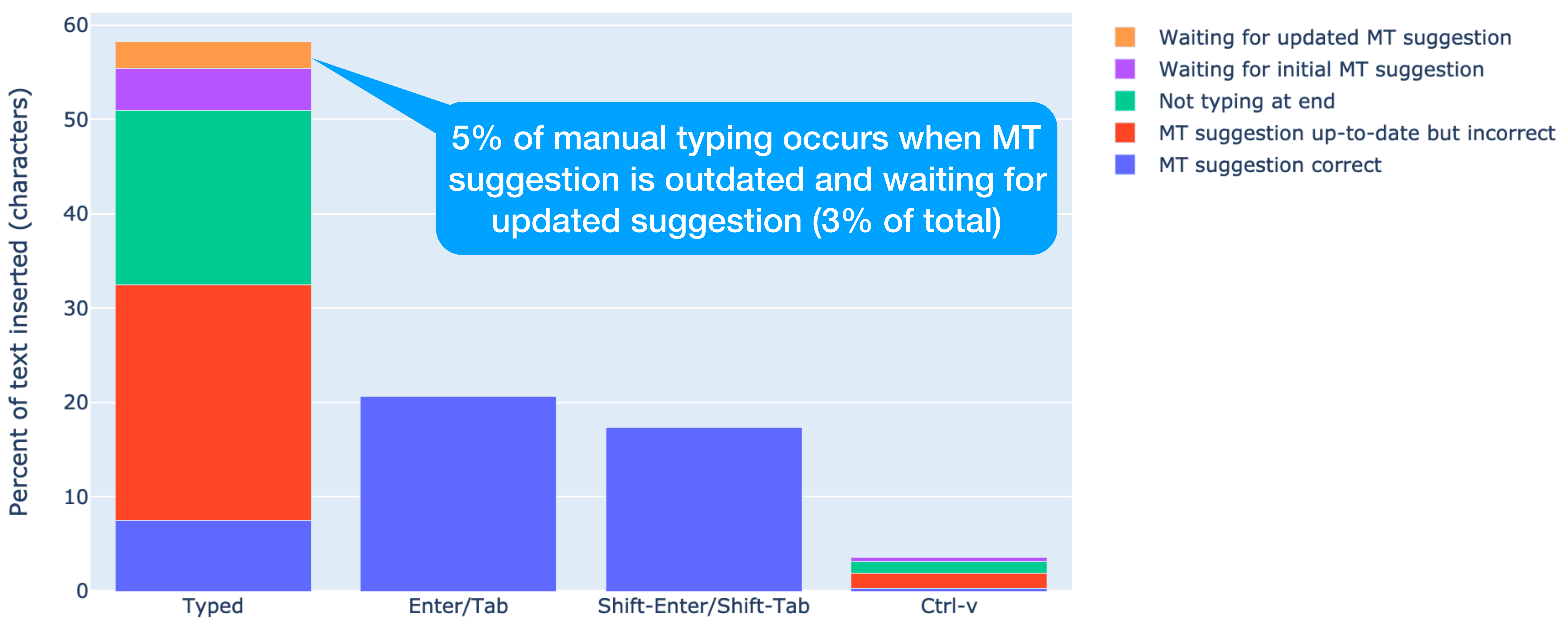
Keys through which text is inserted, broken down by MT state



Keys through which text is inserted, broken down by MT state



Keys through which text is inserted, broken down by MT state



Keys through which text is inserted, broken down by MT state