A New Deal for Translation Quality

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Fellowship & Colloquial Talk

DFKI Berlin, 15.10.2020

First things first: Why do I like machine translation?

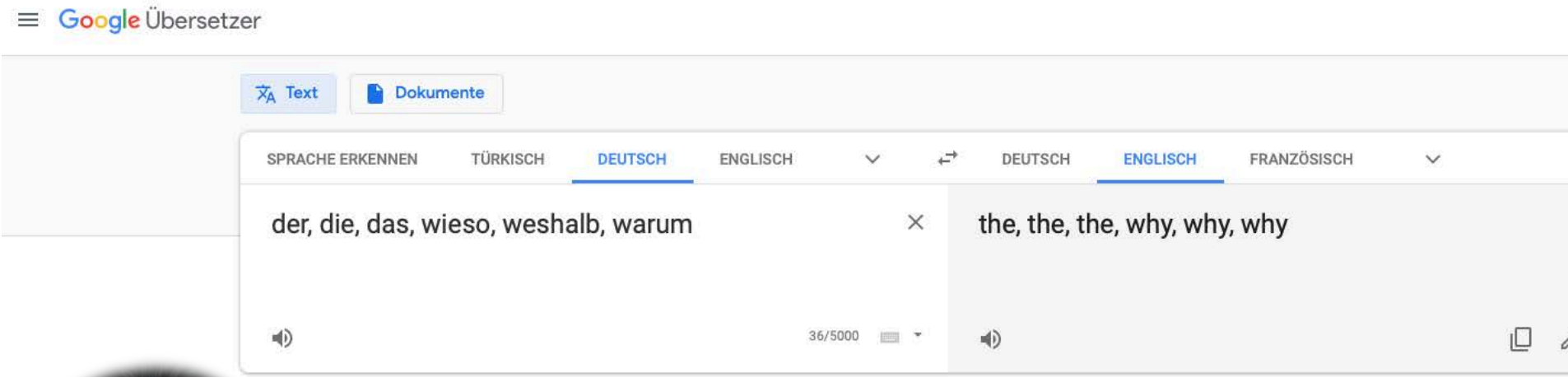
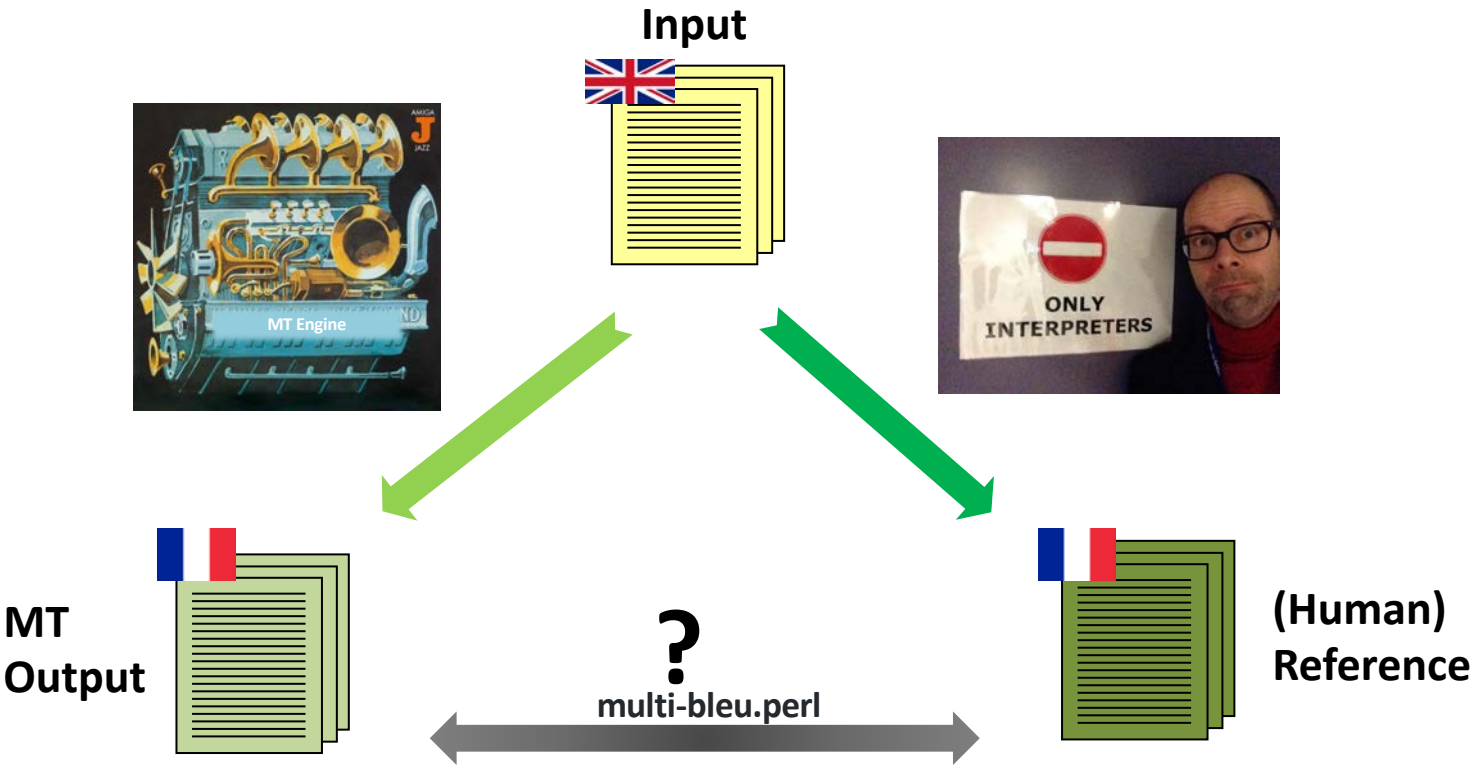


Image: Sesame Workshop

How it all started … back in 2010

Assessing quality in MT development



MT Evaluation is Difficult

- In many NLP tasks, performance can be measured as deviation from some ideal (POS tagging, fact extraction, etc.)
- In MT, this is difficult
  - Theoretical issue: there is **no eternal notion of "good translation"**, MT quality is task-specific: length, target audience, style guide, etc.
  - Practical issue: there are **usually many different good translations**, no simple notion of deviation.
- Example:
  - **Input**: *Use your antivirus to perform a complete scanning.*
  - **MT output**: *Verwenden Sie Ihre Antivirus eine vollständige Abtastung durchzuführen.*
  - **Translator 1**: *Benutzen Sie Ihr Antivirusprogramm, um einen Komplettscan durchzuführen.*
  - **Translator 2**: *Bitte führen Sie mit Ihrem Virenschutzprogramm eine komplette Überprüfung durch.*

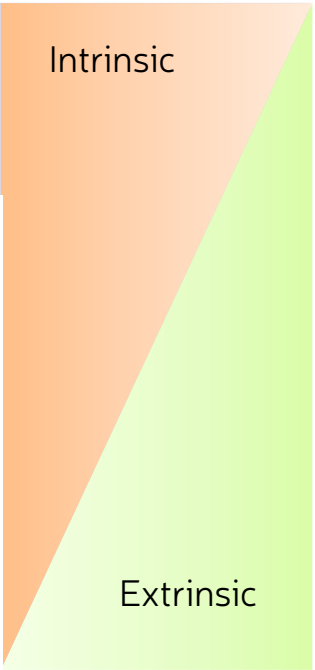
Reference-based assessment of MT output

	Reference-based approach (BLEU etc.)
Assessment of single segments	X
Shows number of errors	X
Shows type of errors	X
Meaningful comparison between different systems, system types, languages	X
Applicable w/o human reference translation	X
Automatic	✓

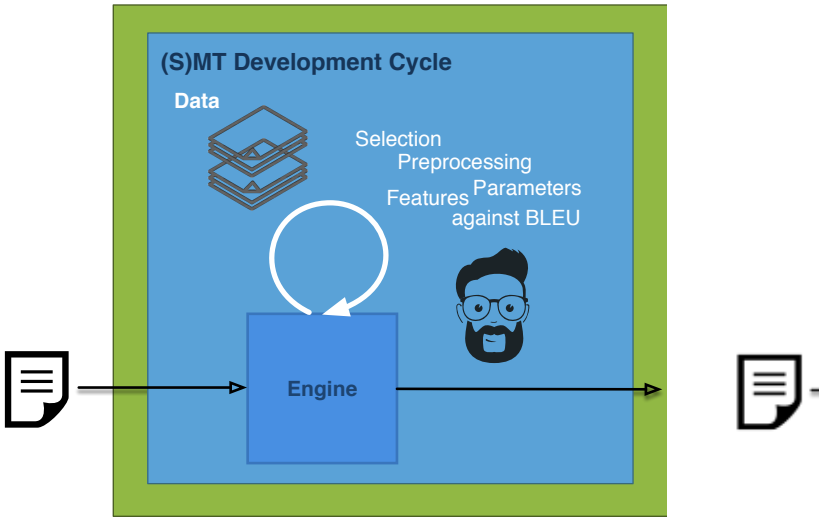
Who needs MT-Evaluation?

	Means	Task-specific?

• **MT Researchers**:
  • Rapid feedback for engineering.
  • Which setting is better?
  • Are differences significant?
	Shallow surface comparison with one (!) reference translation	



Towards a Human-Informed HQMT Development Cycle



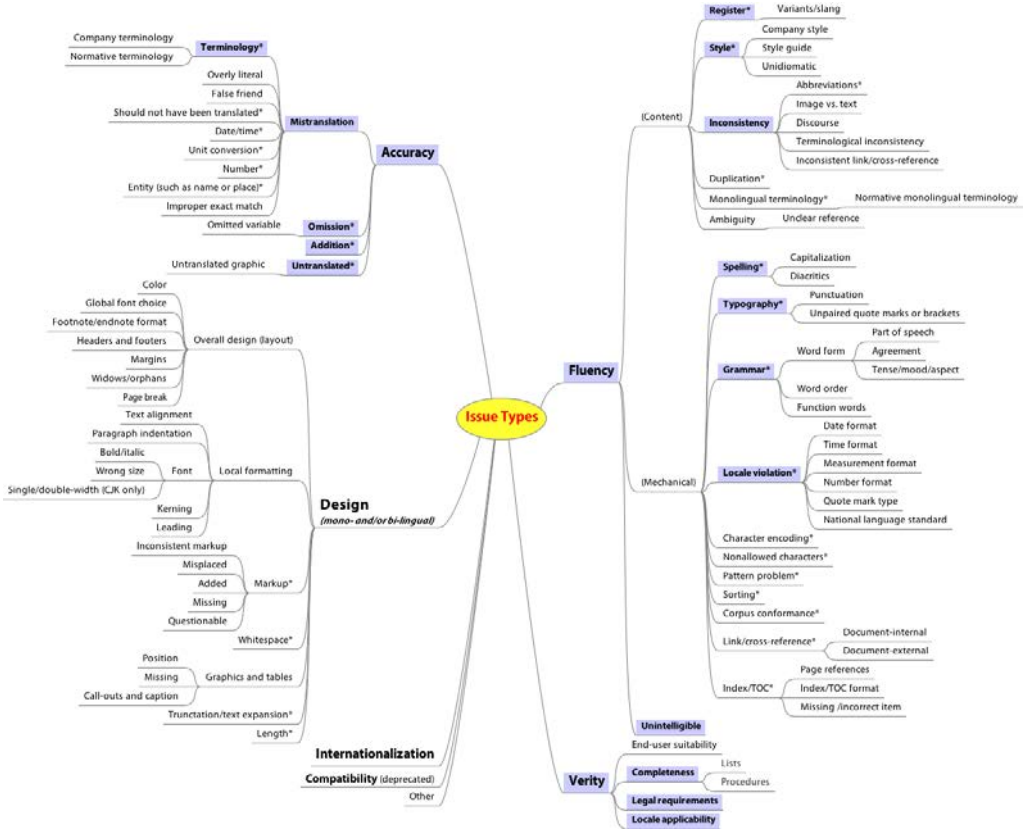
Aljoscha Burchardt, Kim Harris, Georg Rehm, Hans Uszkoreit. **Towards a Systematic and Human-Informed Paradigm for High-Quality Machine Translation** in: Georg Rehm et al. (eds.): Proceedings of the LREC 2016 Workshop "Translation Evaluation", Portorož, Slovenia, o.A., 5/2016

How humans can provide feedback

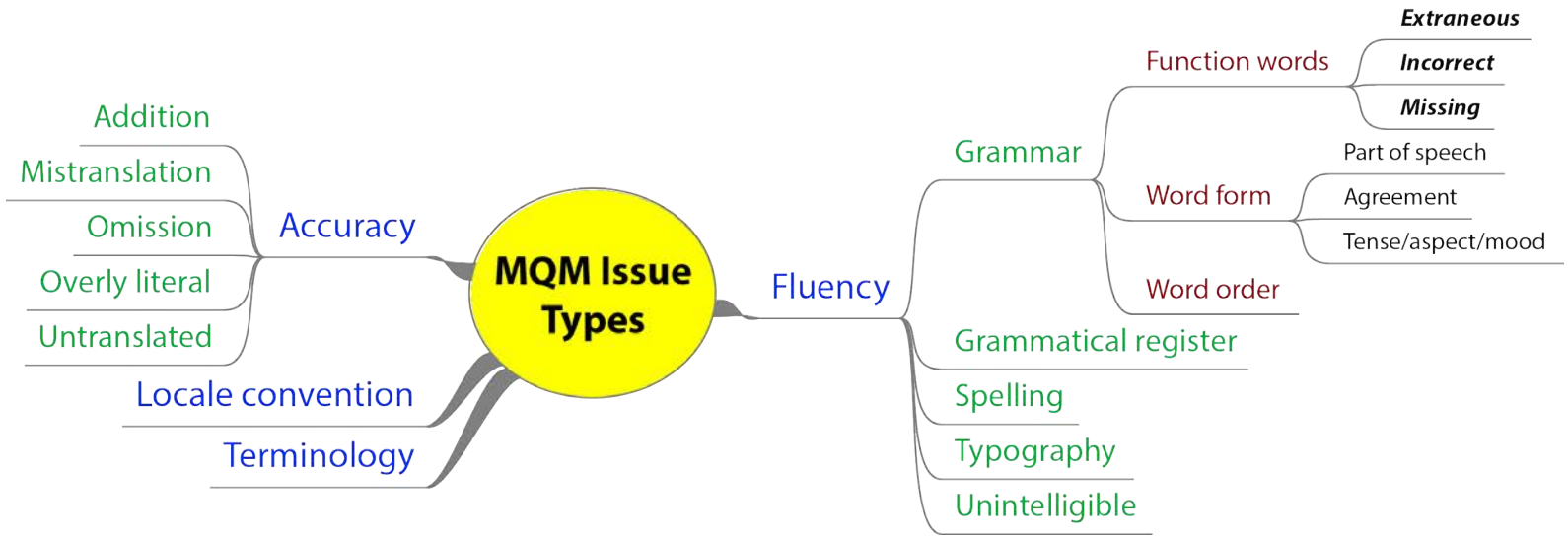
- Analytic error annotation (MQM)
- Task-based evaluation
- Designing test suites

MULTIDIMENSIONAL QUALITY METRICS (MQM)

Full MQM Structure



MT evaluation metric in QT21



- Includes three custom issues
- Heavily tuned to address Grammar issues

MQM annotation example

[a_2050]

Go to Tools and then choose 'Delete browsing history..', you can then choose to delete your Internet cookies.

12 (DE_P1)	**Gehen Sie zu Tools und wählen Sie dann Browsingchronik Löschen.., können Sie dann vorziehen, Ihre Internet-Cookies zu löschen.**		
	deA [[1] Gehen Sie zu] [[2] Tools] und wählen Sie dann [[3] Browsingchronik] [[4] Löschen].., [[5] können] Sie dann [[6] vorziehen], Ihre Internet-Cookies zu löschen.	6	1. **Mistranslation** [Gehen Sie zu] 2. **Untranslated** [Tools] 3. **Mistranslation** [Browsingchronik] 4. **Part of speech** [Löschen] 5. **Word order** [können] 6. **Mistranslation** [vorziehen]
13 (DE_P2)	**Sprung zu Extras und wählen Sie dann Browserverlauf löschen,.., Sie können dann Ihre Internet-Cookies löschen.**		
	deA [[1] Sprung zu] Extras und wählen Sie dann Browserverlauf löschen,..[[2] ,] Sie können dann[[3]]Ihre Internet-Cookies löschen.	3	1. **Mistranslation** [Sprung zu] 2. **Typography** [,] 3. **Omission** [ ]

CAT tools with plugins fort he DQF Framework (thus DQF-MQM): Trados Studio, WorldServer, GlobalLink, SDLTMS, XTM, Kaleidoscope, translate5, and MateCat.

Arle Richard Lommel, Aljoscha Burchardt, Hans Uszkoreit
Multidimensional Quality Metrics (MQM): A Framework for Declaring and Describing Translation Quality Metrics in: Attila Görög, Pilar Sánchez-Gijón (eds.): 3 *Tradumàtica: tecnologies de la traducció volume 0 number 12, Pages 455-463, o.A., 12/2014*

Aljoscha Burchardt, Arle Richard Lommel, Lindsay Bywood, Kimberley Harris, Maja Popovic
Machine translation quality in an audiovisual context
in: Yves Gambier, Sara Ramos Pinto (eds.):
Target volume 28 number 2, Pages 206-221, John Benjamins, 2016

Error profiles by system and language

	DE–EN	EN-DE		EN–LV		EN–CS
Error type	PBMT	PBMT	NMT	PBMT	NMT	PBMT
Accuracy	3	0	0	39	50	0
Addition	539	332	167	277	268	385
Mistranslation	437	967	852	274	677	786
Omission	576	690	355	395	560	588
Untranslated	278	102	24	79	62	301
Fluency	3	0	0	233	210	234
Grammar	0	0	0	11	2	103
Function words	1	2	1	0	0	0
Extraneous	302	525	245	49	49	228
Incorrect	139	804	449	56	55	454
Missing	362	779	231	66	32	348
Word form	0	94	267	280	261	1401
Part of speech	20	128	132	38	35	147
Agreement	18	506	97	419	357	48
Tense/aspect/mood	63	184	51	60	46	397
Word order	218	868	309	336	152	1148
Spelling	118	126	132	324	387	638
Typography	282	553	249	823	387	1085
Unintelligible	0	33	0	10	14	30
Terminology	27	82	139	34	31	0
All categories	3336	6775	3700	3803	3635	8321

Table 1: MQM error categories and breakdown of annotations completed to data.

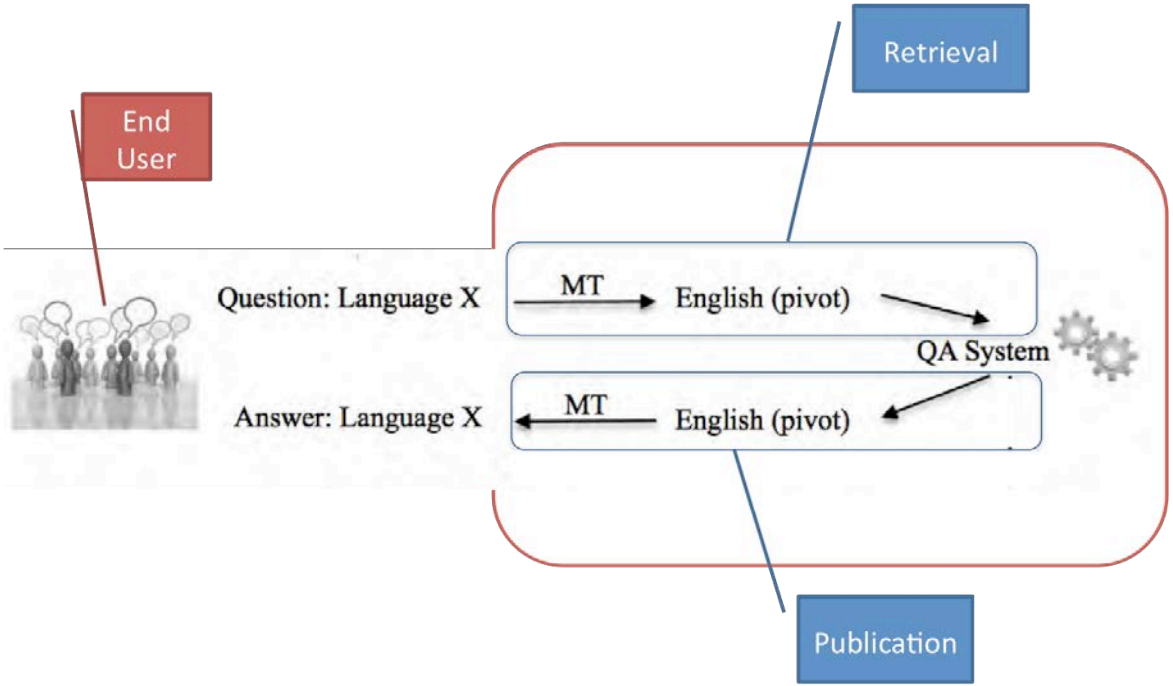
Update

- MQM is currently in the standardization process in ASTM Committee F43 (American Society for Testing and Materials; now known as ASTM International)

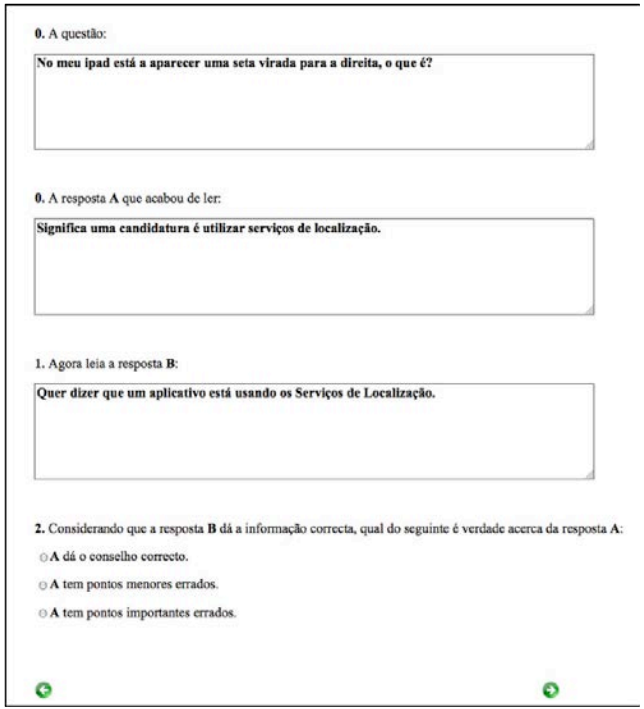
TASK-BASED EVALUATION

Extrinsic Evaluation Scenario

Question: How probable is it that the human operator is being called?



Pilot 0: Emulate Real Usage



- Step 1: Review answer **A** (MT) without any reference:
  - It would clearly help me solve my problem / answer my question
  - It might help, but would require some thinking to understand it.
  - Is not helpful / I don't understand it
- Step 2: Compare answers **A** and **B** (human reference), (re-)evaluate **A** selecting one of the following options:
  - **A** gives the right advice.
  - **A** gets minor points wrong.
  - **A** gets important points wrong.

Estimating operator invention probability

	Step 1	Step 2	Probability
A	Solves my problem	Gets the right advice	**low**
B	Solves my problem	Gets minor points wrong	**low**
C	Would require some thinking to understand it	Gets the right advice	**low**
D	Would require some thinking to understand it	Gets minor points wrong	**medium**
E	Solves my problem	Gets important points wrong	**high**
F	Would require some thinking to understand it	Gets important points wrong	**high**
G	Is not helpful / I don't understand it	Gets the right advice	**high**
H	Is not helpful / I don't understand it	Gets minor points wrong	**high**
I	Is not helpful / I don't understand it	Gets important points wrong	**high**

Probability	EU	BG	CS	NL	DE	PT	ES	Avg.
low	33.3%	47.4%	54.5%	30.4%	47.8%	21.5%	60.4%	42.2%
medium	28.1%	30.6%	17.9%	21.9%	22.0%	15.8%	7.0%	20.5%
high	37.0%	22.0%	27.5%	47.7%	30.1%	62.7%	32.7%	37.1%

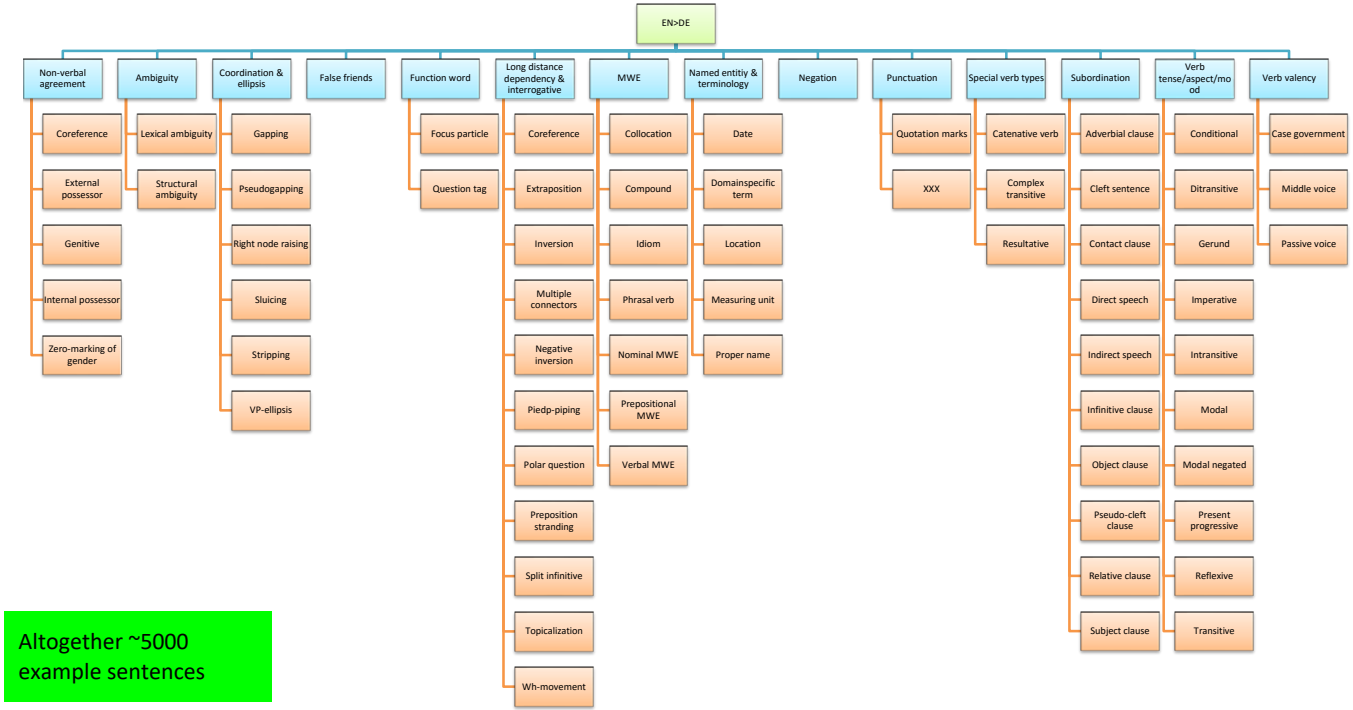
TEST SUITES

Using test suites

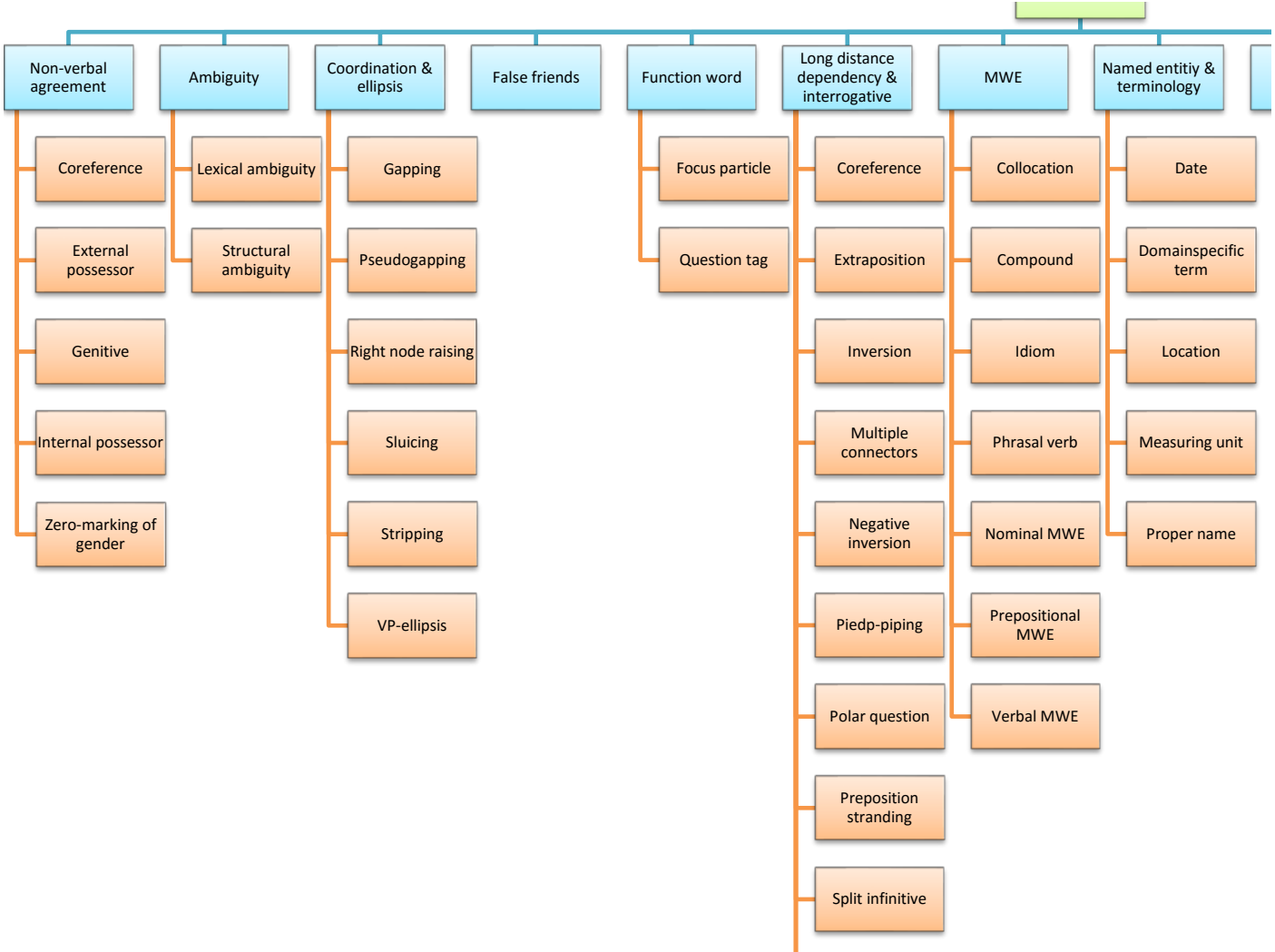
- Test suites are a familiar tool in NLP in areas such as grammar development.
- Idea: Use test suites in MT development.
- Systematically evaluate and compare system(variant)s
    - Gets all 20 imparatives right
    - Gets half of the imparatives right
    - Gets no imparatives rights
    - …
- Guide system improvement / error reduction
- Testing can be local/partial
    - Lexical ambiguity (German "*Gericht*"; English "*court*" vs. "*dish*")
    - Prefix verbs (English "*picked up …*"; German "*hob … auf*")
- Build custom test suites for domain/task/job…

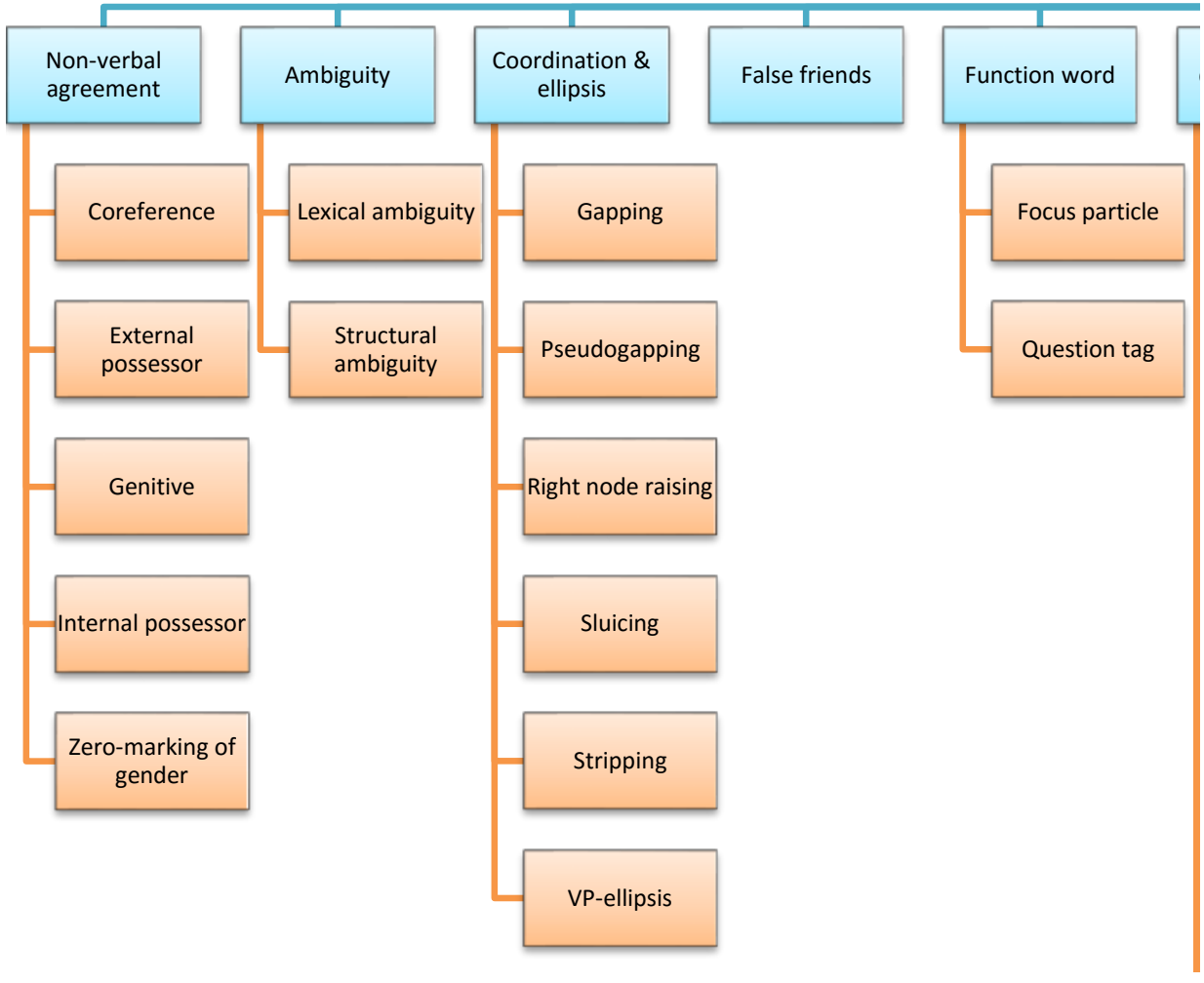
14 Barrier Categories

~ 65 Barriers



Altogether ~5000 example sentences


Non-verbal agreement
Coreference
External possessor
Genitive
Internal possessor
Zero-marking of gender
Ambiguity
Lexical ambiguity
Structural ambiguity
Coordination & ellipsis
Gapping
Pseudogapping
Right node raising
Sluicing
Stripping
VP-ellipsis
False friends
Function word
Focus particle
Question tag
Long distance dependency & interrogative
Coreference
Extraposition
Inversion
Multiple connectors
Negative inversion
Piedp-piping
Polar question
Preposition stranding
Split infinitive
MWE
Collocation
Compound
Idiom
Phrasal verb
Nominal MWE
Prepositional MWE
Verbal MWE
Named entitiy & terminology
Date
Domainspecific term
Location
Measuring unit
Proper name


Non-verbal agreement
Ambiguity
Coordination & ellipsis
False friends
Function word
Coreference
External possessor
Genitive
Internal possessor
Zero-marking of gender
Lexical ambiguity
Structural ambiguity
Gapping
Pseudogapping
Right node raising
Sluicing
Stripping
VP-ellipsis
Focus particle
Question tag

Exemplary test suite entries De-En

Source	Category	Phenomenon	Target (raw)	Target (edited)	Positive token (indicative)	Negative token (indicative)
Lena machte sich früh vom Acker.	MWE	Idiom	Lena [left the field early].	Lena left early.	left early	field
Lisa hat Lasagne gemacht, sie ist schon im Ofen.	Non-verbal agreement	Corefe-rence	Lisa has made lasagna, [she] is already in the oven.	Lisa has made lasagna, it is already in the oven.	it	she
Ich habe der Frau das Buch gegeben.	Verb tense/ aspect/mood	Ditransitive - perfect	I [have] the woman of the Book.	I have given the woman the book.	given the book to the woman, gave the book to the woman, given the woman the book, gave the woman the book	

Test suite experiment – systems used

O-PBMT	Old (phrase-based) version of Google Translate (**o**nline, February 2016)
O-NMT	New (neural) version of Google Translate (**o**nline, November 2016)
OS-PBMT	Open-source phrase-based system (Moses) that uses a default configuration to serve as a baseline (only De-En)
DFKI-NMT	Barebone neural system from DFKI, based on an encoder-decoder neural architecture with attention
ED-NMT	Neural system from U Edinburgh, system was built using the Nematus toolkit
RWTH-NMT	NMT-system from RWTH, makes use of subword units and has been finetuned to perform well on the IWSLT 2016 spoken language task (only De-En)
RBMT	Commercial rule-based system Lucy

Test suite experiment – examples: ambiguity

(1)	Source:	Er hat einen Kater, weil er sehr tierlieb ist.
	Reference:	He has a cat because he is very fond of animals.
	Google-old:	He has a hangover, because he is very fond of animals.
	Google-new:	He has a cat because he is very fond of animals.
	RBMT:	He has a tomcat because it is very animal-dear.
	OS-PBMT:	He has a hangover because it is an encounter.
	DFKI-NMT:	He has a kater because he is very animal.
	RWTH-NMT:	He has a hangover because he‘s very animal.
	ED-NMT:	He has a hangover because he is very animal-loving.

Test suite experiment – examples: phrasal verb

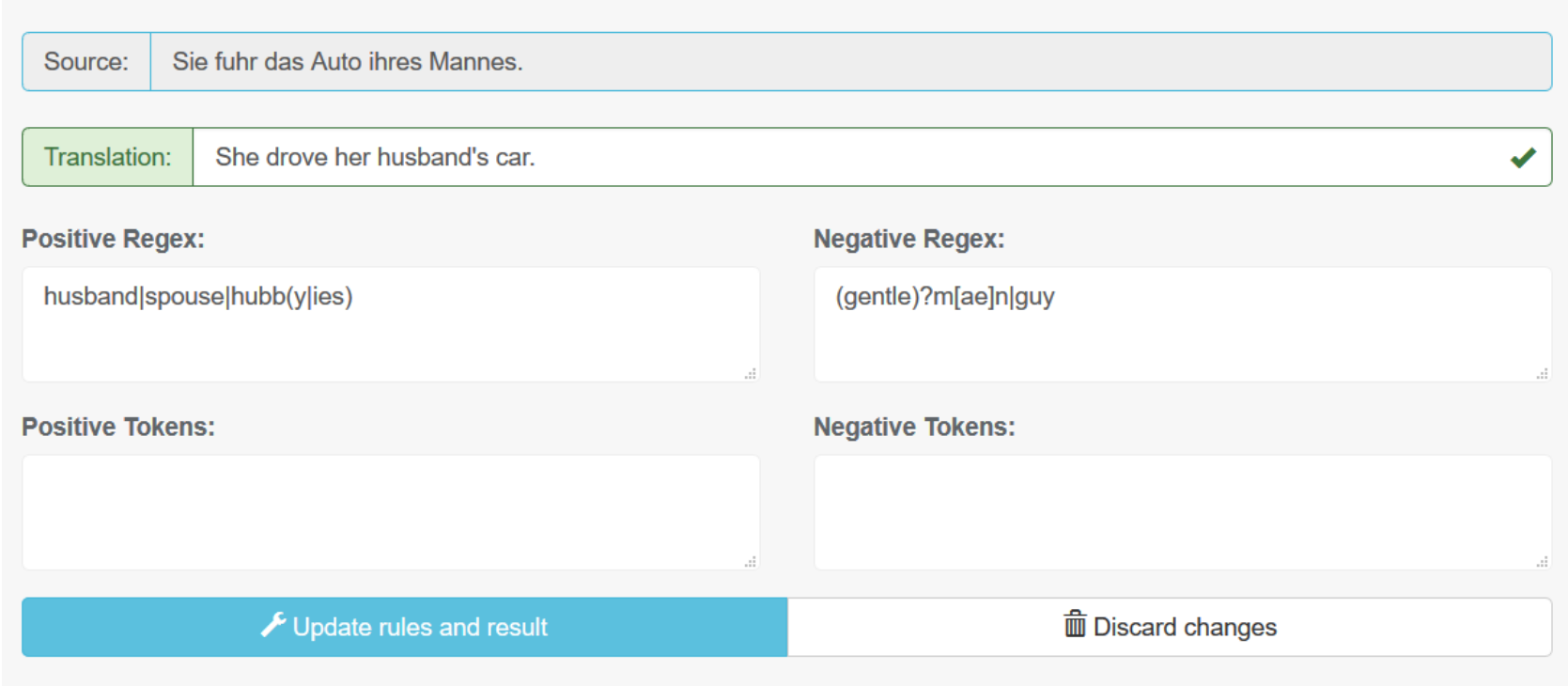
(2)	Source:	Warum hörte Herr Muschler mit dem Streichen auf?
	Reference:	Why did Mr. Muschler stop painting?
	Google-old:	Why heard Mr. Muschler on with the strike?
	Google-new:	Why did Mr. Muschler stop the strike?
	Update 2020:	Why did Mr. Muschler stop painting?
	RBMT:	Why did Mr. Muschler stop with the strike?
	OS-PBMT:	Why was Mr Muschler by scrapping on?
	DFKI-NMT:	Why did Mr. Muschler listen to the rich?
	RWTH-NMT:	Why did Mr. Muschler listen to the stroke?
	ED-NMT:	Why did Mr. Muschler stop with the stump?

Test suite experiment – examples: MWE

(7)	Source:	Die Arbeiter müssten in den sauren Apfel beißen.
	Reference:	The workers would have to bite the bullet.
	Google-old:	The workers would have to bite the bullet.
	Google-new:	The workers would have to bite into the acid apple.
	Update 2020:	The workers would have to bite the bullet.
	RBMT:	The workers would have to bite in the acid apple.
	OS-PBMT:	The workers would have to bite the bullet.
	DFKI-NMT:	Workers would have to bite in the acid apple.
	RWTH-NMT:	The workers would have to bite into the clean apple.
	ED-NMT:	The workers would have to bite in the acidic apple.

TEST SUITE AUTOMATION

Regular Expressions



Semi-automatic evaluation

Apply Tokens 0 | Skip Tokens

	ID data point	Source	Category	Phenomenon	Translation
⚠	00005001	Er hob die Tür aus den Angeln.	Ambiguity	Lexical ambiguity	He lifted the door.
✔	00005002	Die Tür hing schief in den Angeln.	Ambiguity	Lexical ambiguity	The door hung obliquely in the hinges.
✖	00005003	Die Angeln der Tür quietschten beim Öffnen.	Ambiguity	Lexical ambiguity	The angling of the door creaked open.

Update & Thanks

Eleftherios Avramidis, Vivien Macketanz, Ursula Strohriegel, Aljoscha Burchardt, Sebastian Möller

Fine-grained linguistic evaluation for state-of-the-art Machine Translation

In: Proceedings of the Fifth Conference on Machine Translation (WMT-2020)

Eleftherios Avramidis, Vivien Macketanz, Ursula Strohriegel, Hans Uszkoreit

Linguistic evaluation of German-English Machine Translation using a Test Suite

In: Proceedings of the Fourth Conference on Machine Translation (WMT-2019)

Vivien Macketanz, Eleftherios Avramidis, Aljoscha Burchardt, Hans Uszkoreit

Fine-grained evaluation of German-English Machine Translation based on a Test Suite

In: Proceedings of the Third Conference on Machine Translation (WMT-2018)

category	#	JHU	MLLP	onlA	onlB	onlG	onlY	RWTH	UCAM	UEDIN	avg
Ambiguity	74	-2.7	21.6	4.1	0.0	4.1	10.8	-1.3	2.7	12.1	6.9
Composition	42	4.8	0.0	14.3	0.0	9.5	2.4	-2.4	-4.7	7.1	5.2
Coordination and ellipsis	23	8.7	-4.4	0.0	0.0	13.1	0.0	0.0	-13.1	0.0	7.3
False friends	34	-3.0	5.8	0.0	3.0	-5.9	23.6	5.9	-5.8	14.7	6.8
Function word	41	-2.5	7.3	4.9	0.0	41.4	0.0	-7.4	-2.4	9.7	12.5
LDD & interrogatives	38	10.6	10.6	-2.7	0.0	5.3	0.0	0.0	5.3	7.9	5.6
MWE	53	5.6	7.5	5.7	0.0	1.9	1.9	3.8	-1.8	3.8	4.7
Named entity and terminology	34	5.9	3.0	5.9	0.0	-3.0	-5.9	8.9	0.0	5.9	0.3
Negation	19	0.0	0.0	0.0	0.0	42.1	0.0	0.0	0.0	-10.5	6.6
Non-verbal agreement	48	12.5	10.4	12.5	0.0	22.9	2.1	-2.1	0.0	12.5	9.7
Punctuation	51	5.9	2.0	-21.6	0.0	-7.9	1.9	27.5	0.0	23.5	8.0
Subordination	31	3.3	6.5	-6.5	3.2	19.4	3.2	6.5	0.0	0.0	5.0
Verb tense/aspect/mood	3995	-4.0	-5.9	12.9	0.2	19.8	1.6	5.6	-7.6	5.1	6.0
Verb valency	30	10.0	0.0	0.0	0.0	13.4	6.6	0.0	0.0	3.4	5.8
average (items)	4513	-3.1	-4.3	11.6	0.2	18.7	2.0	5.3	-6.8	5.4	6.1
average (categories)		3.9	4.6	2.1	0.5	12.6	3.4	3.2	-2.0	6.8	6.5

Table 2: Percentage (%) of accuracy improvement or deterioration between WMT18 and WMT19 for all the systems submitted (averaged in last column) and the systems submitted with the same name

That’s it

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