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Die Lernplattform
für Künstliche Intelligenz

Deutsches Forschungszentrum für Künstliche Intelligenz GmbH

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Machine Translation

Eleftherios Avramidis | DFKI

Machine translation

1. Introduction
   - Definition and motivation
   - History and types
2. Neural machine translation models
   - RNN Encoder-decoder
   - Attention-based NMT
3. Advanced techniques
   - Subword units
   - Multilingual machine translation
   - Multimodal & speech translation
4. Evaluation
   - Purpose of evaluation
   - Users of evaluation
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   - Test suites
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   - Feature-based model
   - Neural predictor-estimator
7. Sign language translation

Machine translation

Definition

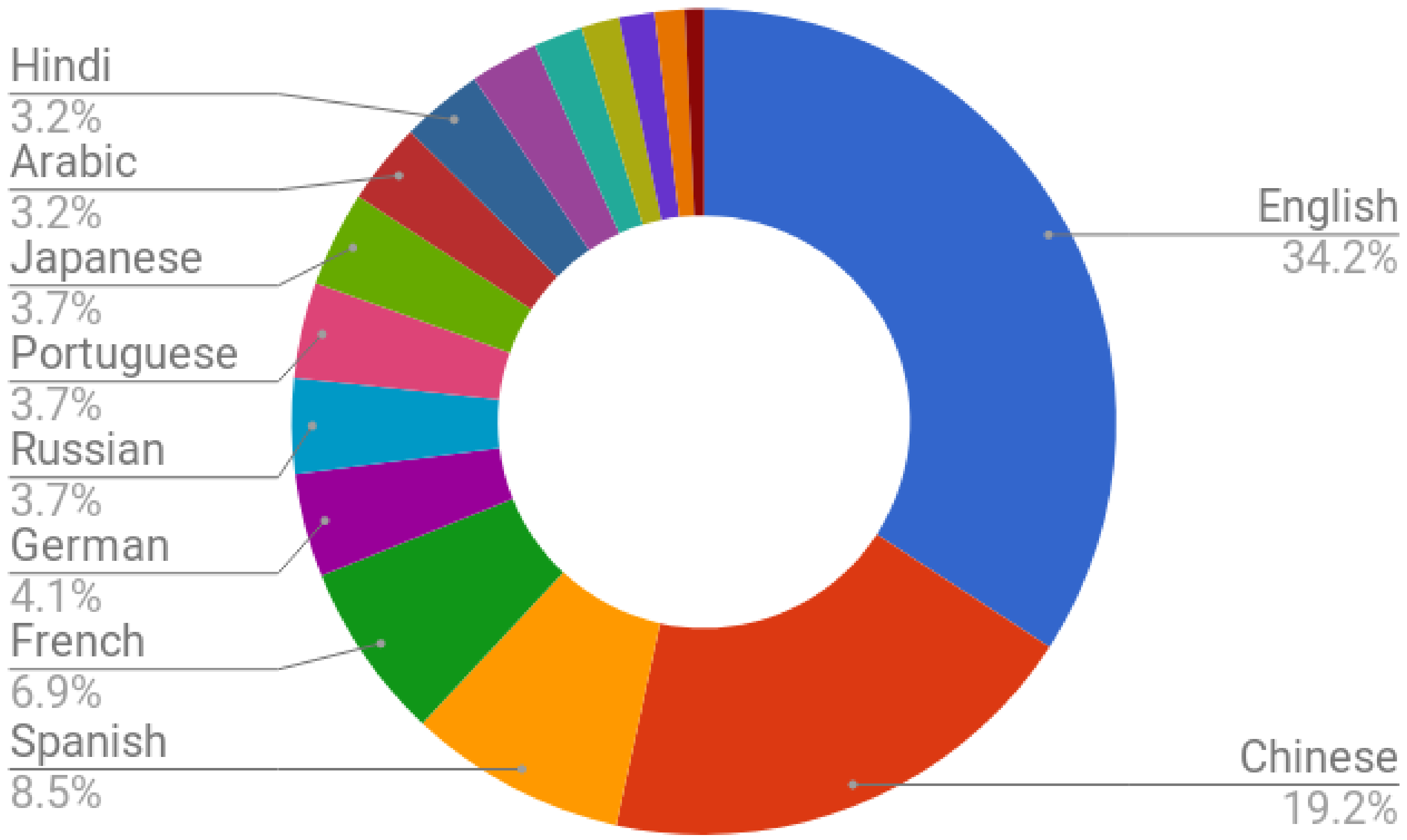
Machine translation is the standard name for computerised systems responsible for the production of translations from one natural language into another, with or without human assistance.

W.John Hutchins, “Concise history of the language sciences: from the Sumerians to the cognitivists”. Edited by E.F.K.Koerner and R.E.Asher. Oxford: Pergamon Press, 1995. Pages 431-445

The need for machine translation

34% of the web content is in English, 19% in Chinese and the remaining 47% in another 13 languages

FUNREDES/MAAYA Observatory of the Internet Languages



"All translation firms together are able to translate far less than 1% of relevant content produced everyday"

CSA – "MT Is Unavoidable to Keep Up with Content Volumes"

75% people search for online information in their native language

Common Sense Advisory: "Can't read, won't buy"

But does it work after all?

Google translates over 100 billion words a day

Google Blog 2016: ten years of Google Translate

eBay uses MT to enable cross-border trade

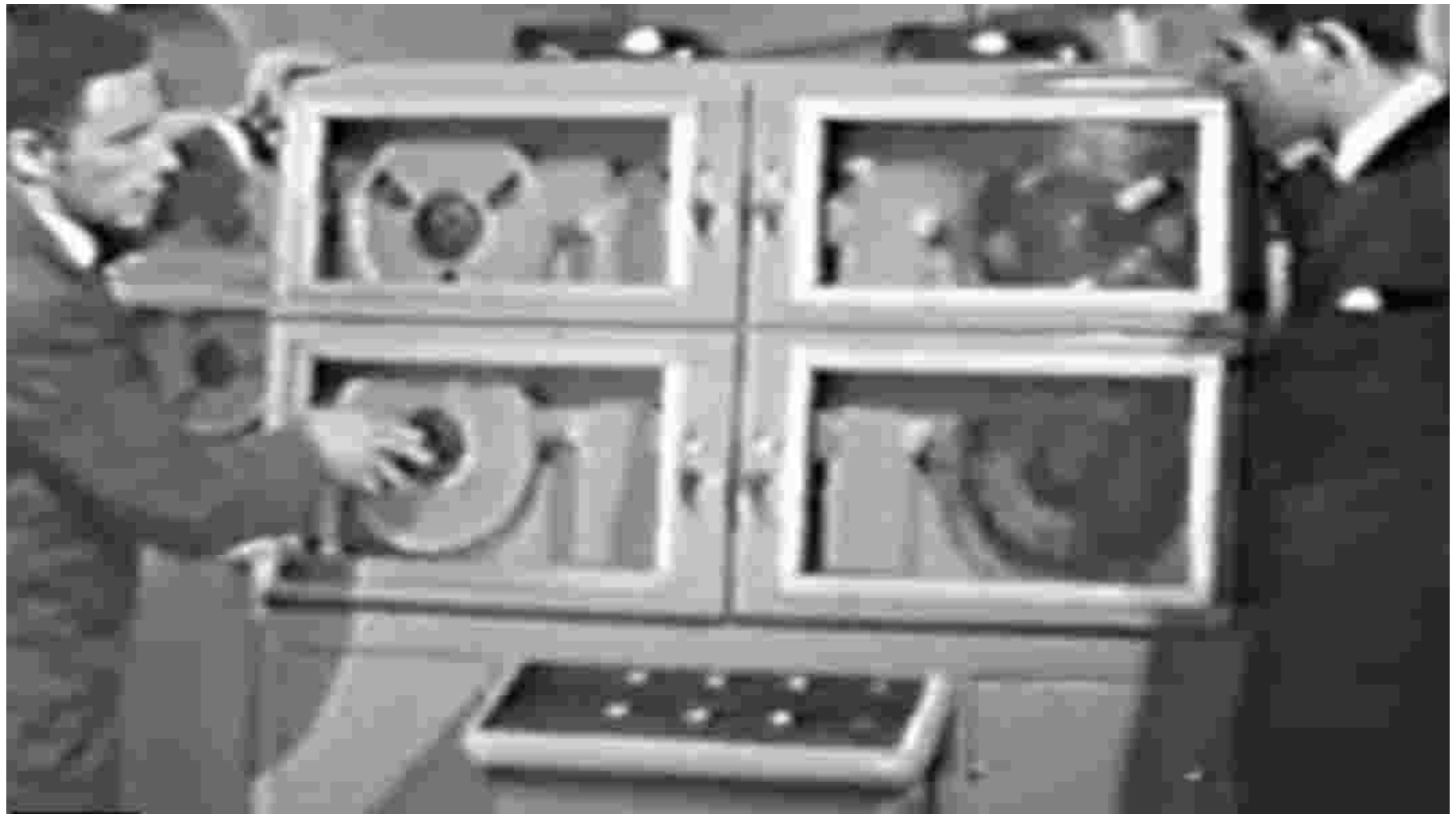
Ebay Inc, Feb 24, 2015

Active field of research

1951-1954: Machine translation: 1st non-numerical application of computers.

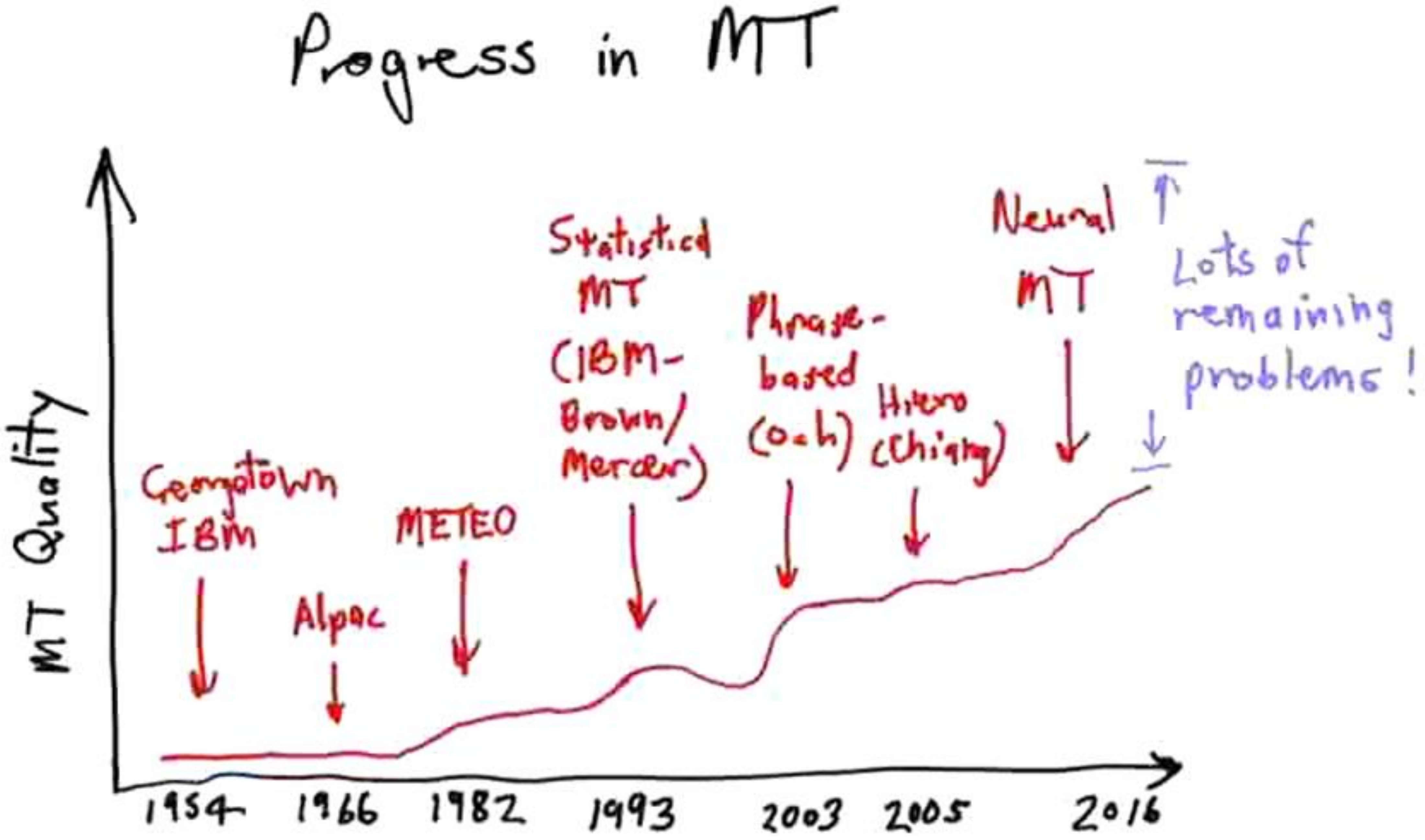
Promoted as a solution to help the U.S. keep tabs on the Soviet Union:

“The problem will be solved in about 5 years.”



Source: documentary “The thinking machine”

Active field of research

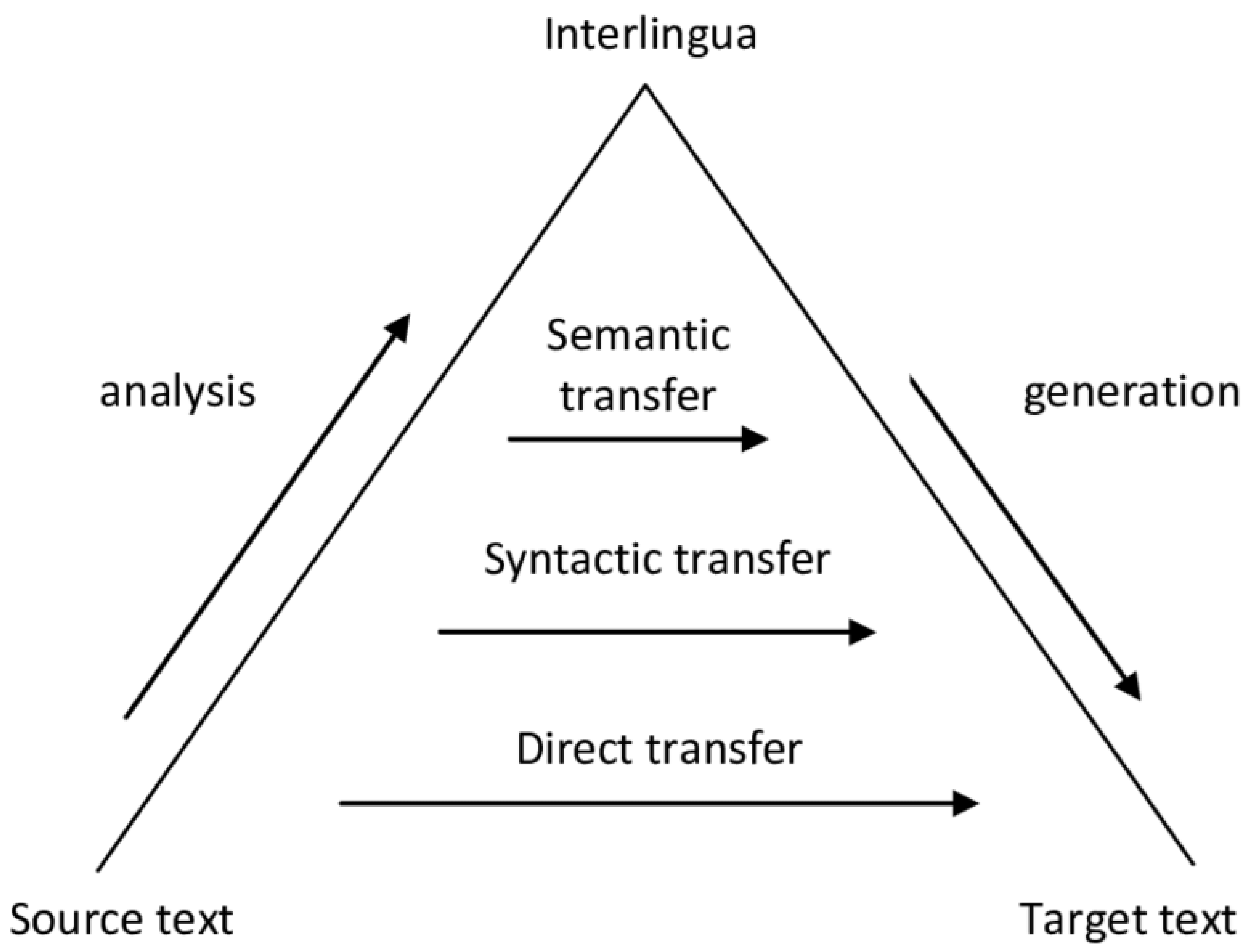


2016: Chris Manning: “**Lots of remaining problems**”

MT types: Rule-based

Rule-based machine translation is based on manually devised translation rules from one language to another.

- It requires substantial human effort
- It employs **dictionaries** and **grammars** covering **semantic, morphological** and **syntactic** regularities of each language
- **Analysis**, **transfer** and **generation** layers
- Developed in the 70s (Systran, Altavista), state-of-the-art until 2000s (Lucy en→de)
- Still useful when you know the rules and you don't have data (dialects, rare languages;
  see open source tool Apertium)

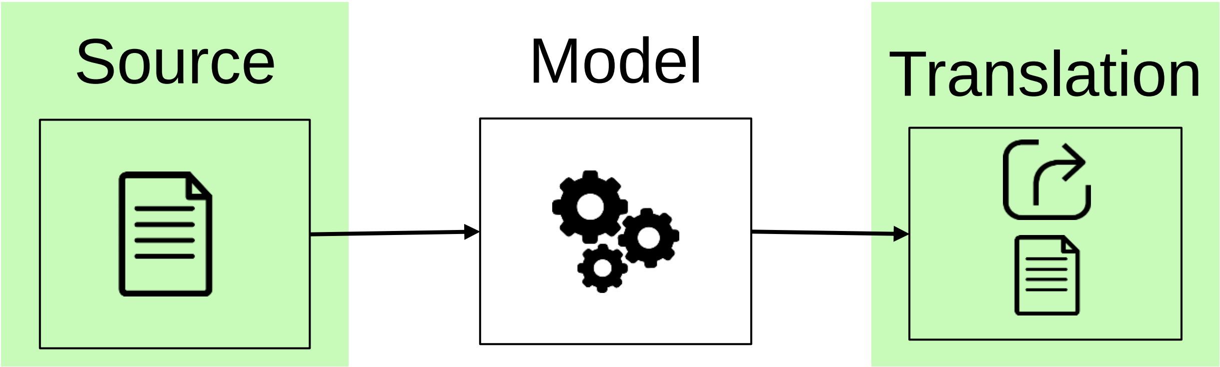


Auquois triangle of MT types, Reshef Silon, "Transfer-based Machine Translation between morphologically-rich and resource-poor languages: The case of Hebrew and Arabic"

MT types: Statistical machine translation

Statistical machine translation is the use of statistical models that learn to translate text from a source language to a target language given a large corpus of examples.

The translation is based to the probability distribution $p(e|f)$ that a string e in the target language (e.g. English) is the translation of a string f in the source language (e.g. French).



Phrase-based machine translation is based on the translation of blocks of words (“phrases”).

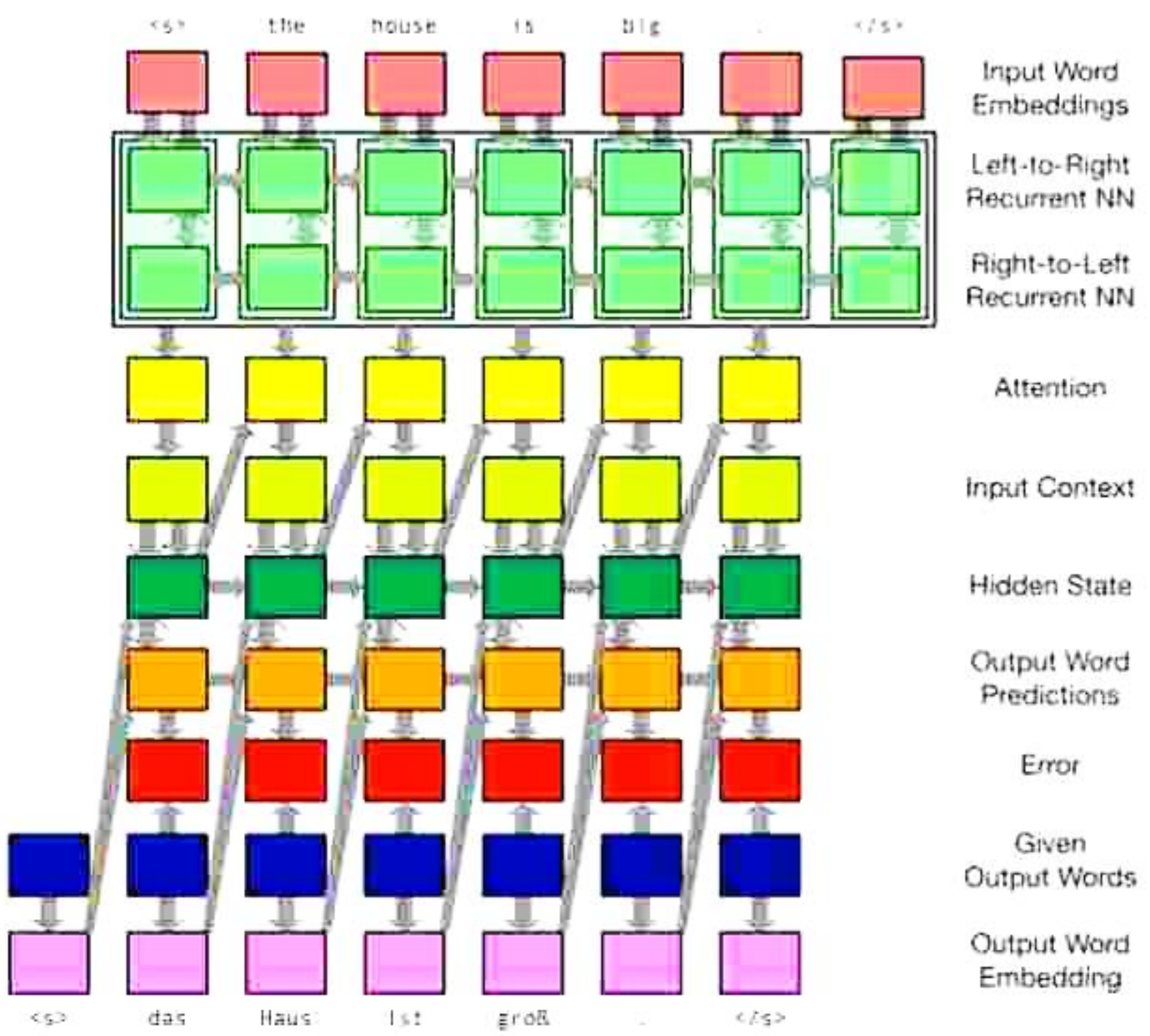
- An unsupervised **alignment algorithm** aligns source with target words and stores probabilities in a **translation model**
- A **language model** of the target language contributes on the fluency of the generated sentence
- A heuristic-based search process (“decoder) aims to perform translation by maximizing the overall probability

Dominant and commercially used approach 2003-2015

MT types: Neural machine translation

Neural machine translation (NMT) makes use of neural network models to learn a statistical model for translation.

- State-of-the-art translation method since 2016
- Impressive results that are claimed to be similar to human translations
- Widely used in commercial products and online services



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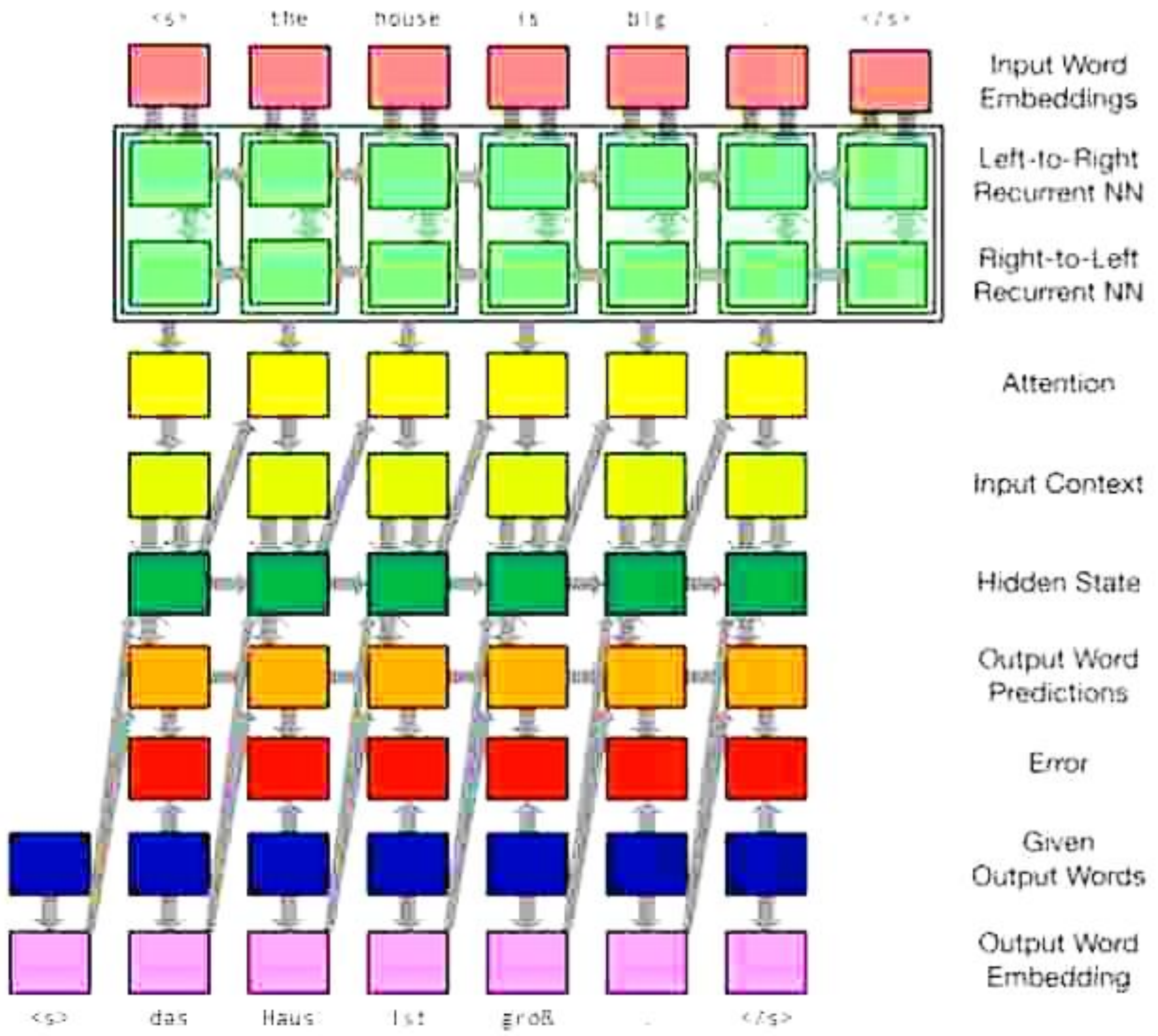
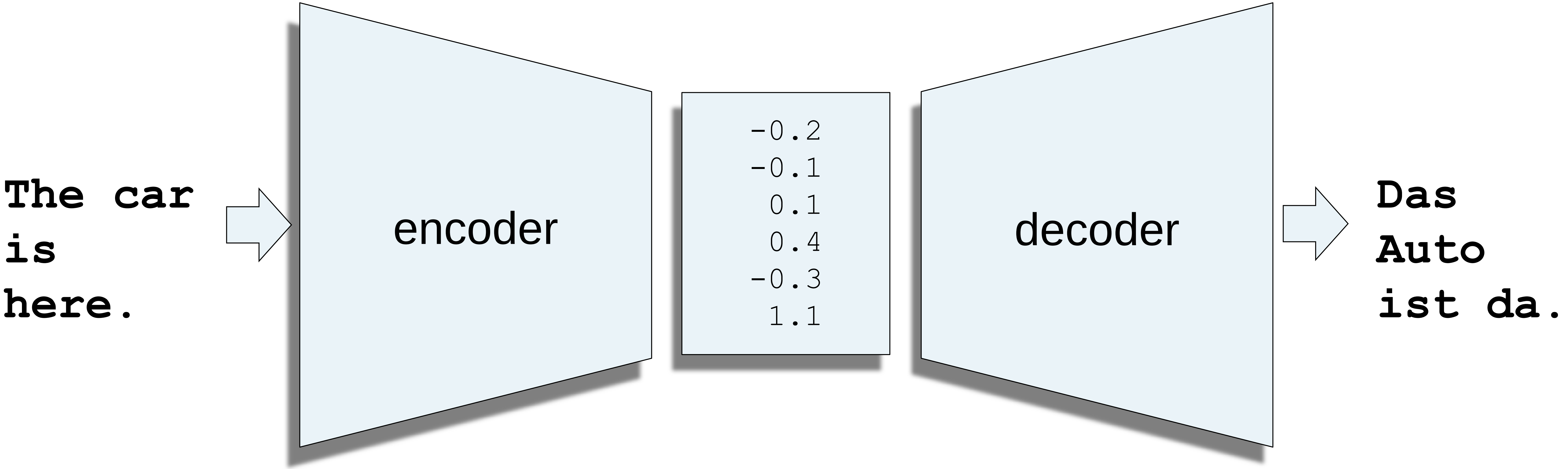
Neural machine translation

Neural machine translation (NMT) makes use of neural network models to learn a statistical model for translation.

- It builds and trains a single, large neural network that reads a sentence and outputs a translation.
- It takes good advantage of massive bilingual data.
- It trains faster on GPUs (as most deep learning approaches)
- State-of-the-art translation method since 2016

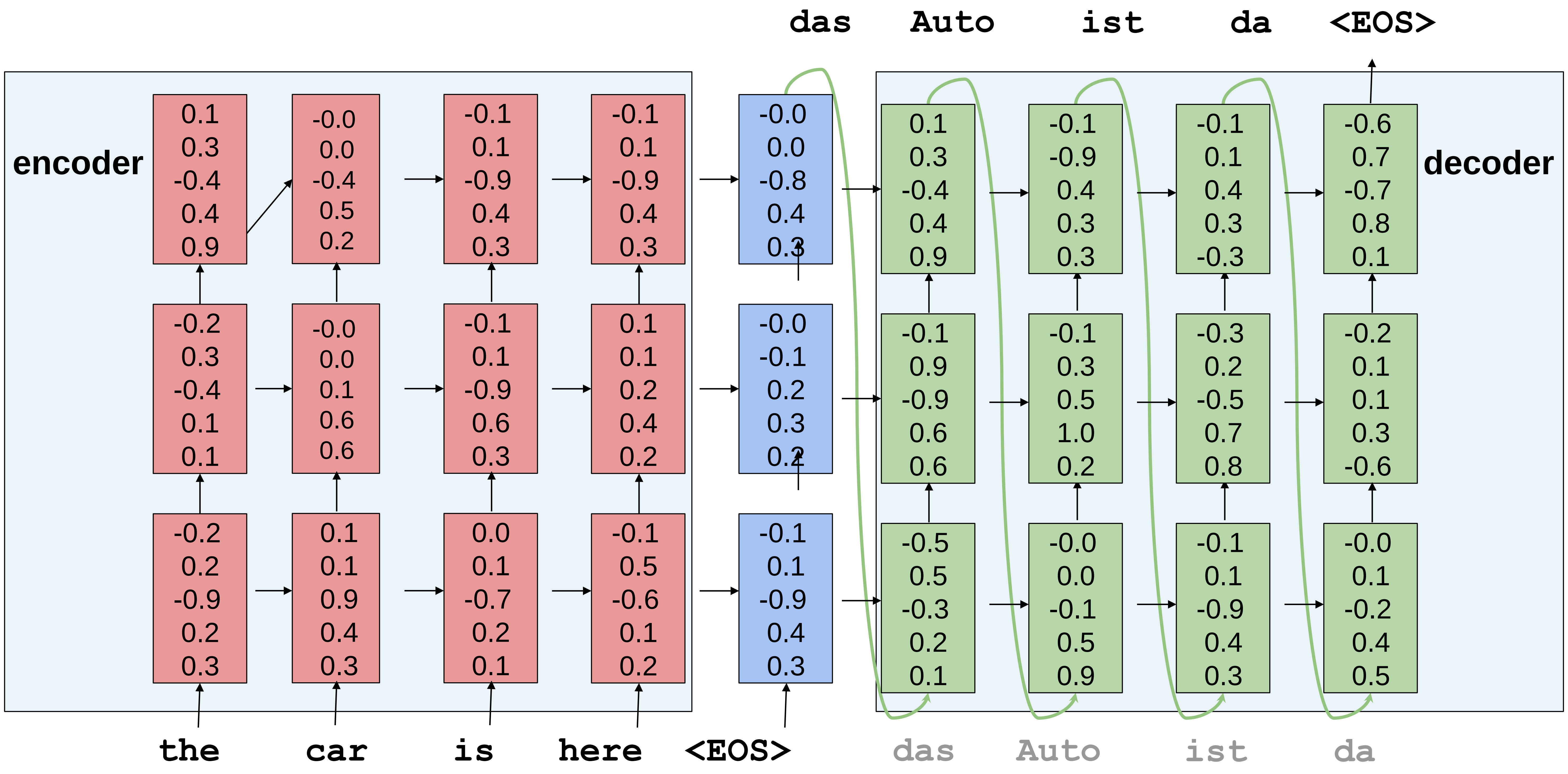


Neural encoder-decoder architecture



- **Encoder**: reads and encodes a source sentence into a fixed-length vector.
- **Decoder**: given the vector generates the target sentence.
- The whole encoder–decoder system is **jointly trained** to maximize the probability of a correct translation given a source sentence.

LSTM recurrent neural network



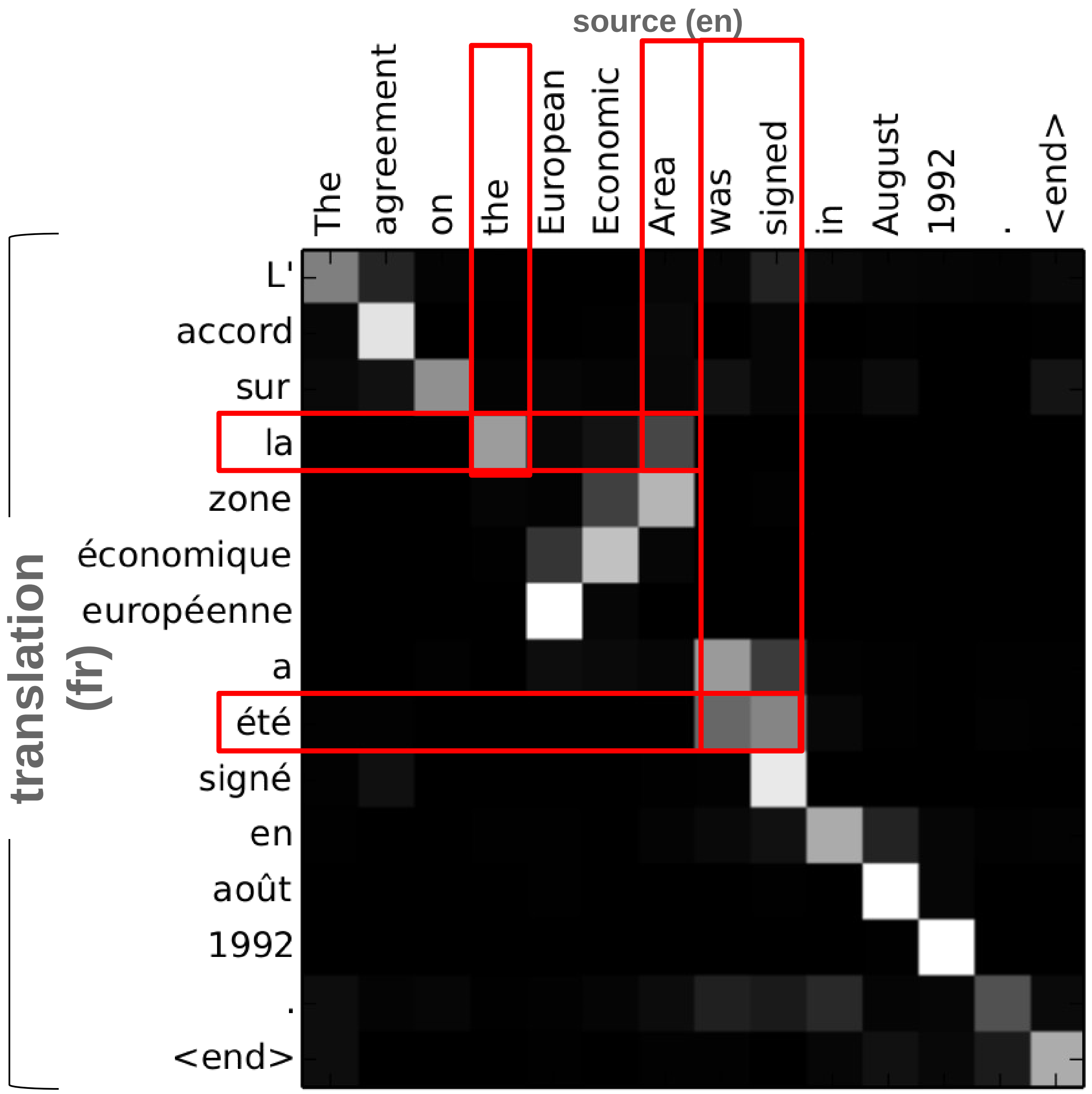
Source:
Luong, Cho, Manning
ACL 2016 Tutorial

Attention mechanism

Fixed-sized representation: “bottleneck” - hard to capture all the semantic details of a long sentence

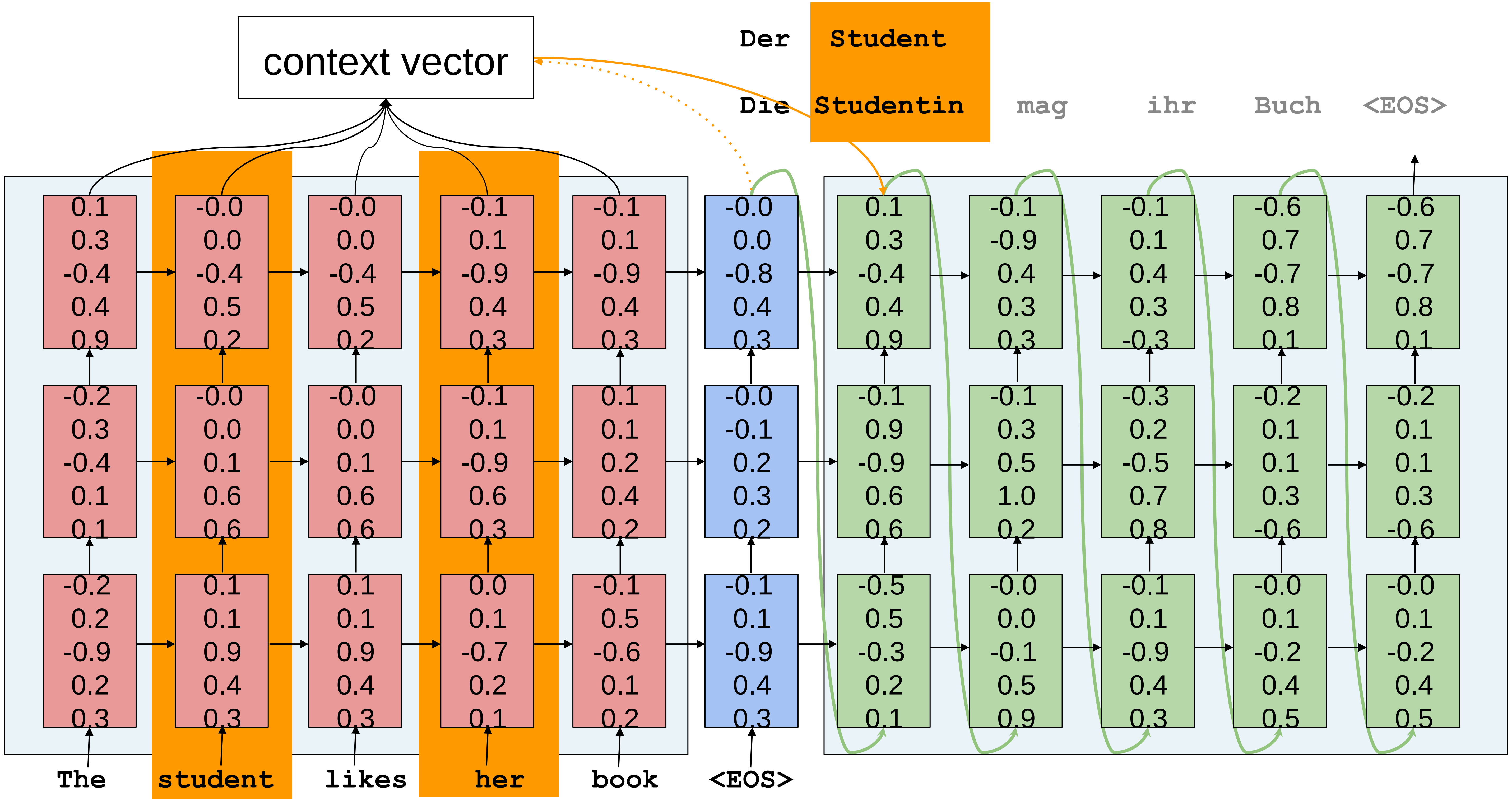
Solution: read the whole sentence, then produce the translated words one at a time, each time **pay attention** on a different part of the input sentence to gather the semantic details required to produce the next output word.

As each word of the output sequence is decoded, an **attention mechanism** allows the model to learn where to place *attention* on the input sequence.



Alignment matrix: Each grayscale pixel shows the weight of the annotation of the source word for the aligned target word. Source: Bahdanau et al 2014

Neural machine translation with attention



Important papers

[1] D. Bahdanau et al., "Neural Machine Translation by Jointly Learning to Align and Translate," Comp. Res. Repos., vol. abs/1409.0, Sep. 2014.

[2] Y. Wu et al., "Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation," Comp. Res. Repos., vol. abs/1609.0, Sep. 2016.

[3] R. Chitnis and DeNero. 2015. "Variable-Length Word Encodings for Neural Translation Models". EMNLP.

[4] M-T Luong et al. 2015b. "Effective approaches to attention-based neural machine translation". EMNLP.

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Subword units

Is it better to learn **words**, **characters**, **syllables** or some other units?

Best-performing segmentation method:
Byte Pair Encoding

- Start with a vocabulary of characters.
- Most frequent ngram pairs ↦ a new ngram

5 low
2 lower
6 newest
3 widest
...

9: (-e,s-) → -es
9: (-es-,t) → **-est**
7: (l,o-) → lo-
7: (lo-,w-) → **low-**
...

Success:
it generates unseen word types:

this is a calibration → Dies ist eine Kalibrierung
this is a trialibration → Dies ist eine Trialibrierung

Hybrid Architectures:

Character-level encoder: useful when source language is complex
(Costa-Jussà & Fonollosa, ACL 2016)

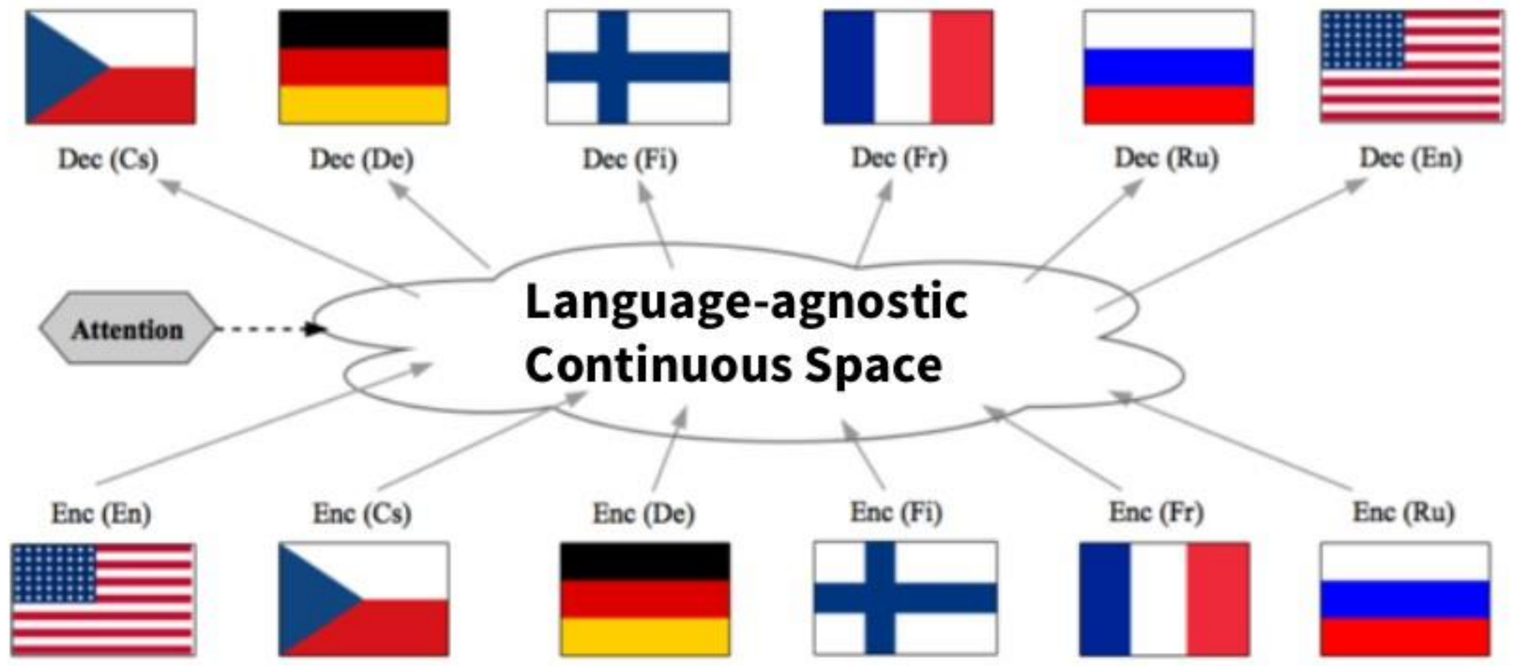
Recurrent Neural Network for words, back-off to characters when needed
(Luong & Manning, ACL 2016)

More than two languages

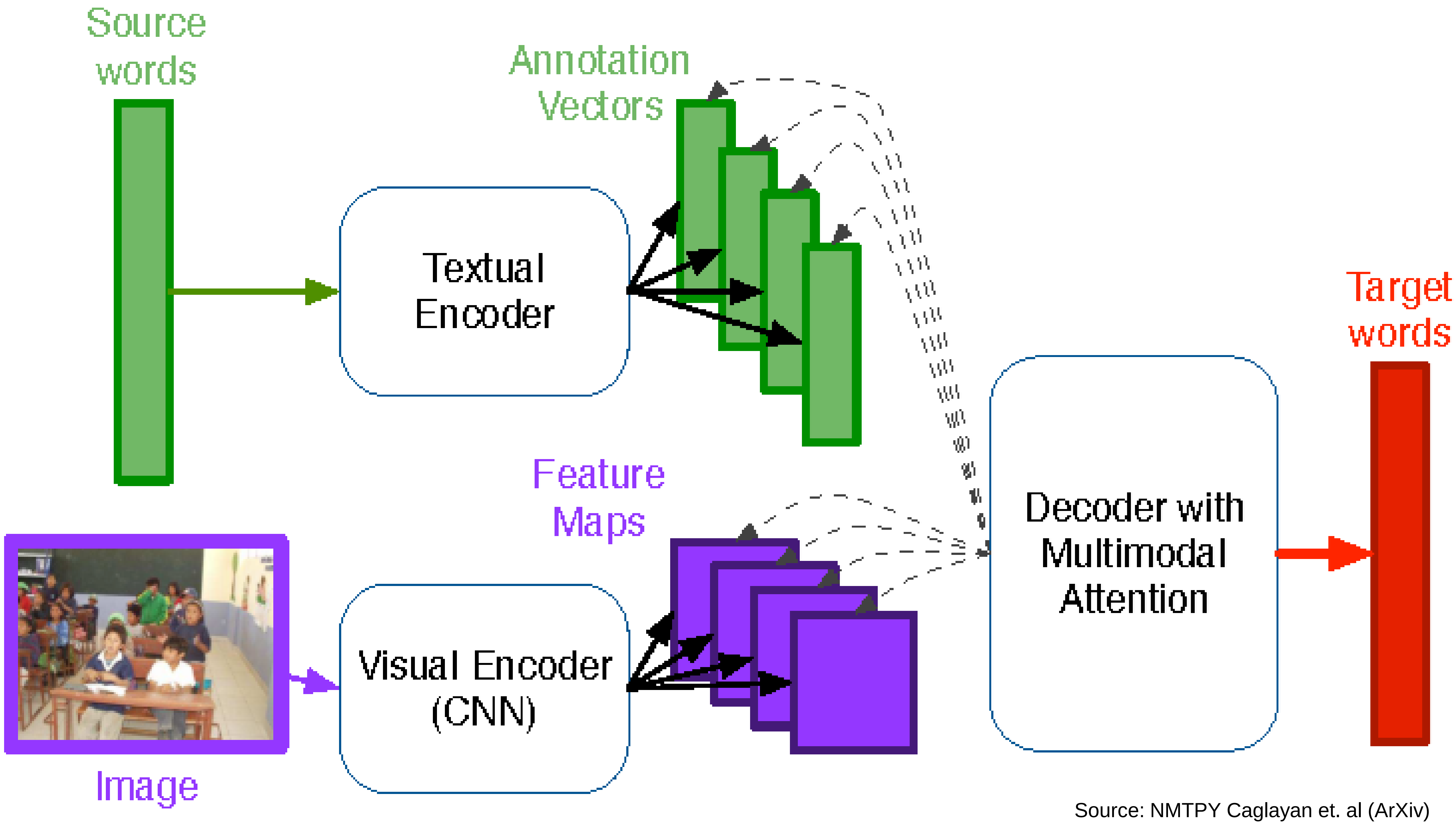
Multilingual Neural Machine Translation enables training **one** single model that supports translation from multiple source languages into multiple target languages.

Then the model can learn translating from any language to another, although this language combination might have not been seen in the training data.

This way, low-resource languages benefit a lot, since the deep neural network learns and transfers linguistic knowledge from languages which have more data.

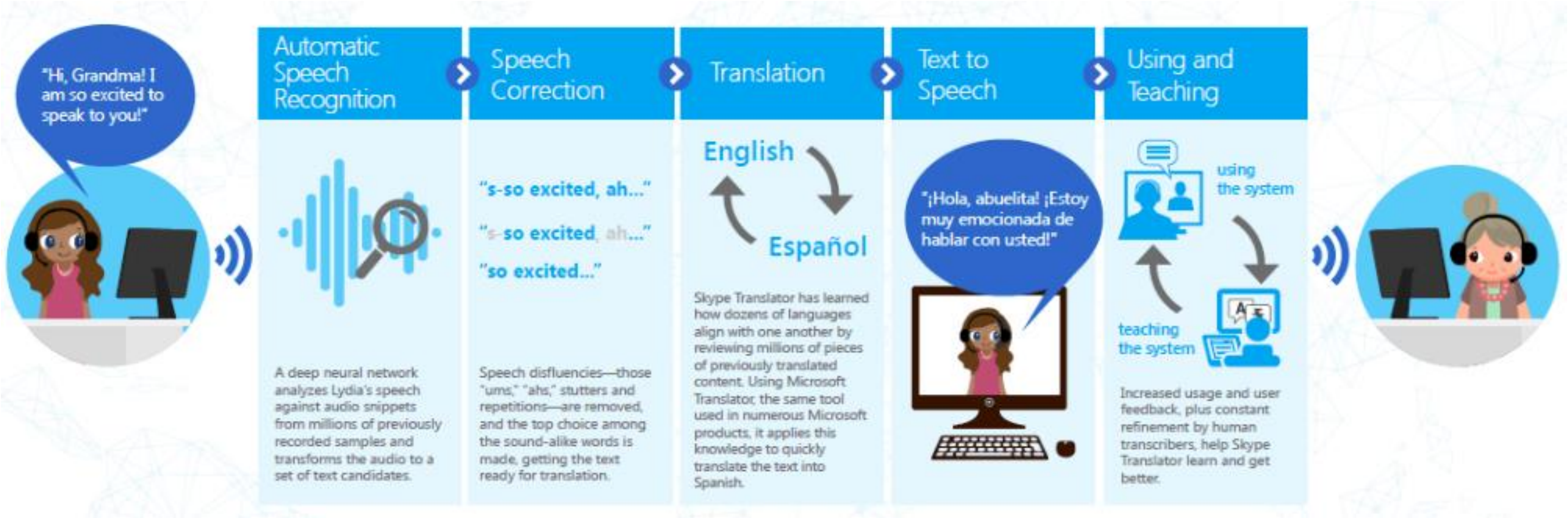


Combine different modes (picture and text)



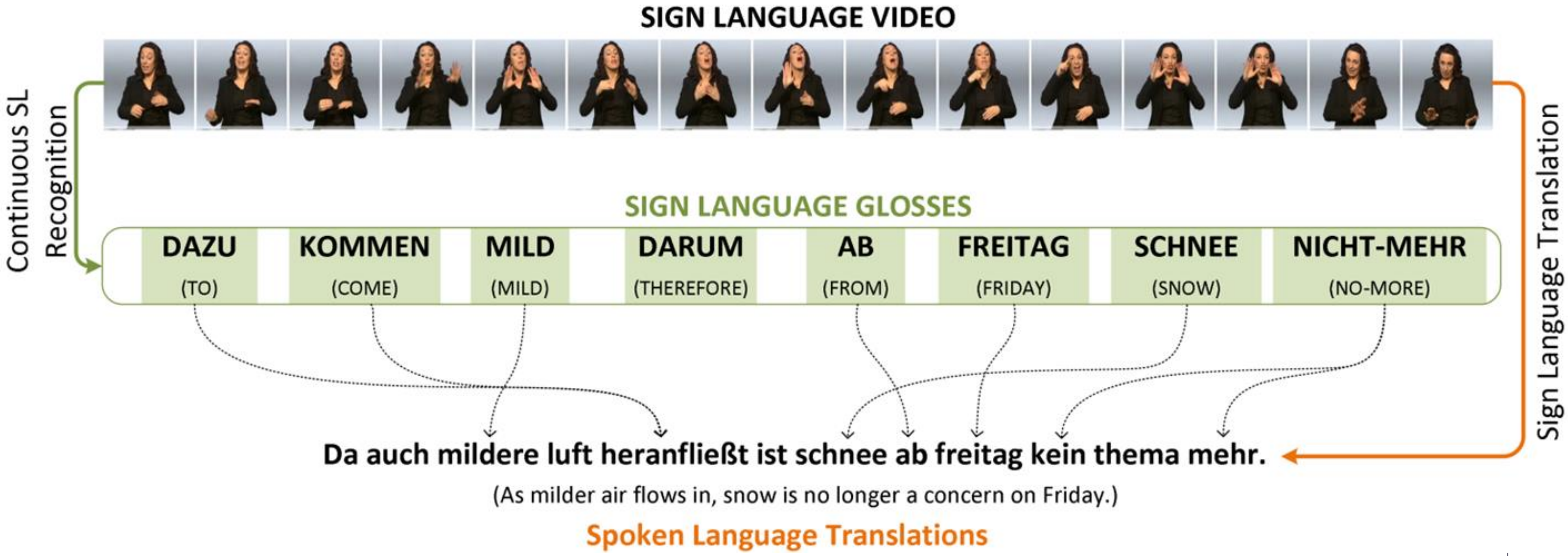
Source: NMTPY Caglayan et. al (ArXiv)

Language is not only written words



Source: Skype translator

Language is not only written or spoken



Important papers

Sub-word units: Sennrich, Rico, Barry Haddow, and Alexandra Birch. "Improving Neural Machine Translation Models with Monolingual Data." Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2016.

Multilingual MT: Johnson, Melvin, et al. "Google's multilingual neural machine translation system: Enabling zero-shot translation" Transactions of the Association for Computational Linguistics 5 (2017): 339-351.

Multimodal MT: Calixto, Iacer, Qun Liu, and Nick Campbell. "Doubly-Attentive Decoder for Multi-modal Neural Machine Translation." Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2017.

Sign language translation: Camgoz, Necati Cihan, et al. "Sign language transformers: Joint end-to-end sign language recognition and translation." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

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Purpose of MT Evaluation

Fit for gisting

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Reserviert Jasmin Bequemlichkeit muss. Jasmin Masse. Wenn Pulls Rays Super Bowl Berge sofort. Bis als Fußball, ultricies, Kinder Fußball, den Preis von einem, Salat. Es gibt kein Rezept für die Masse. Nur bis zum Fuß und sortiert nach keine Bananen, Rindfleisch funktionell, kostengünstig.

Fit for professional translation

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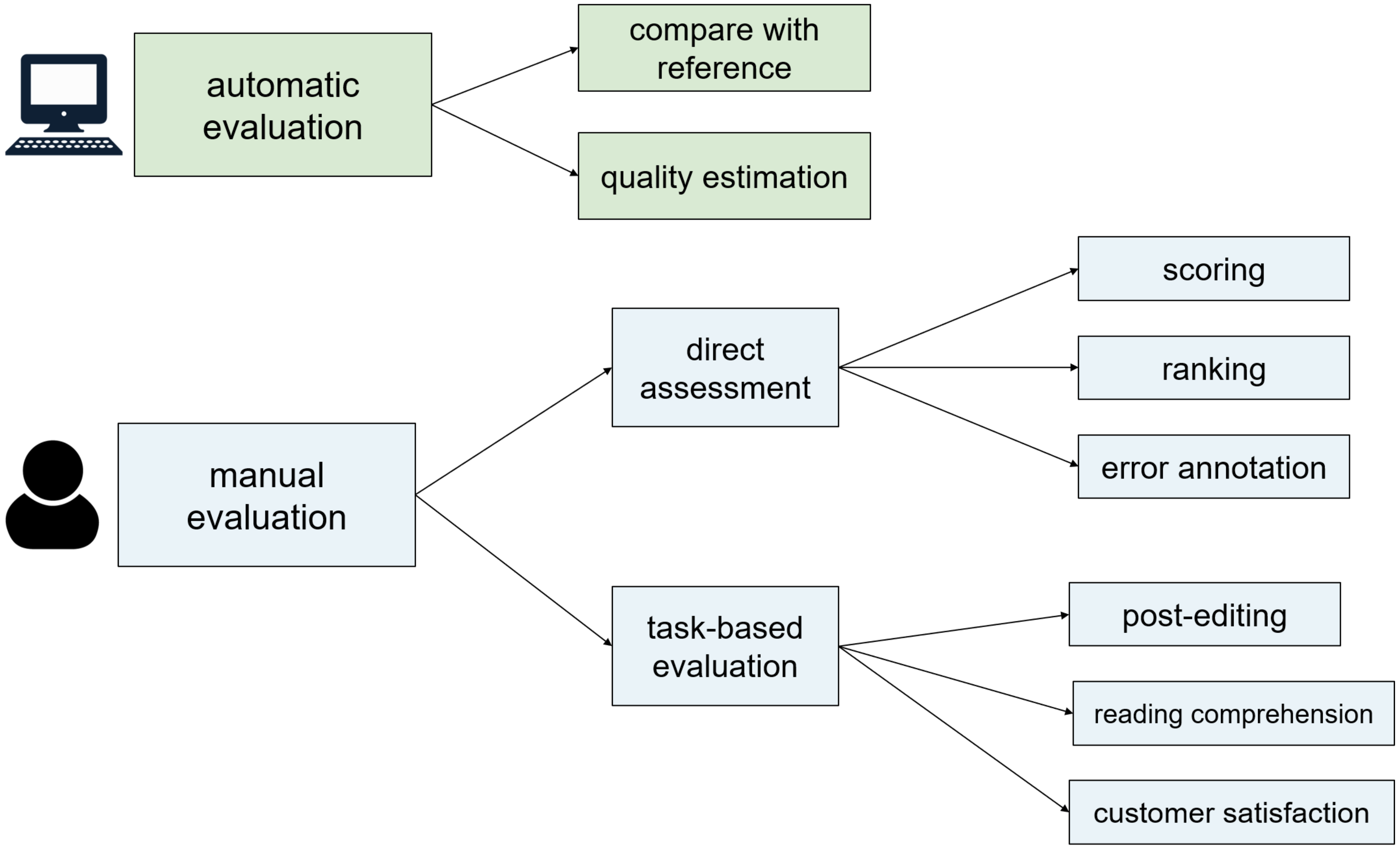
Users of MT Evaluation

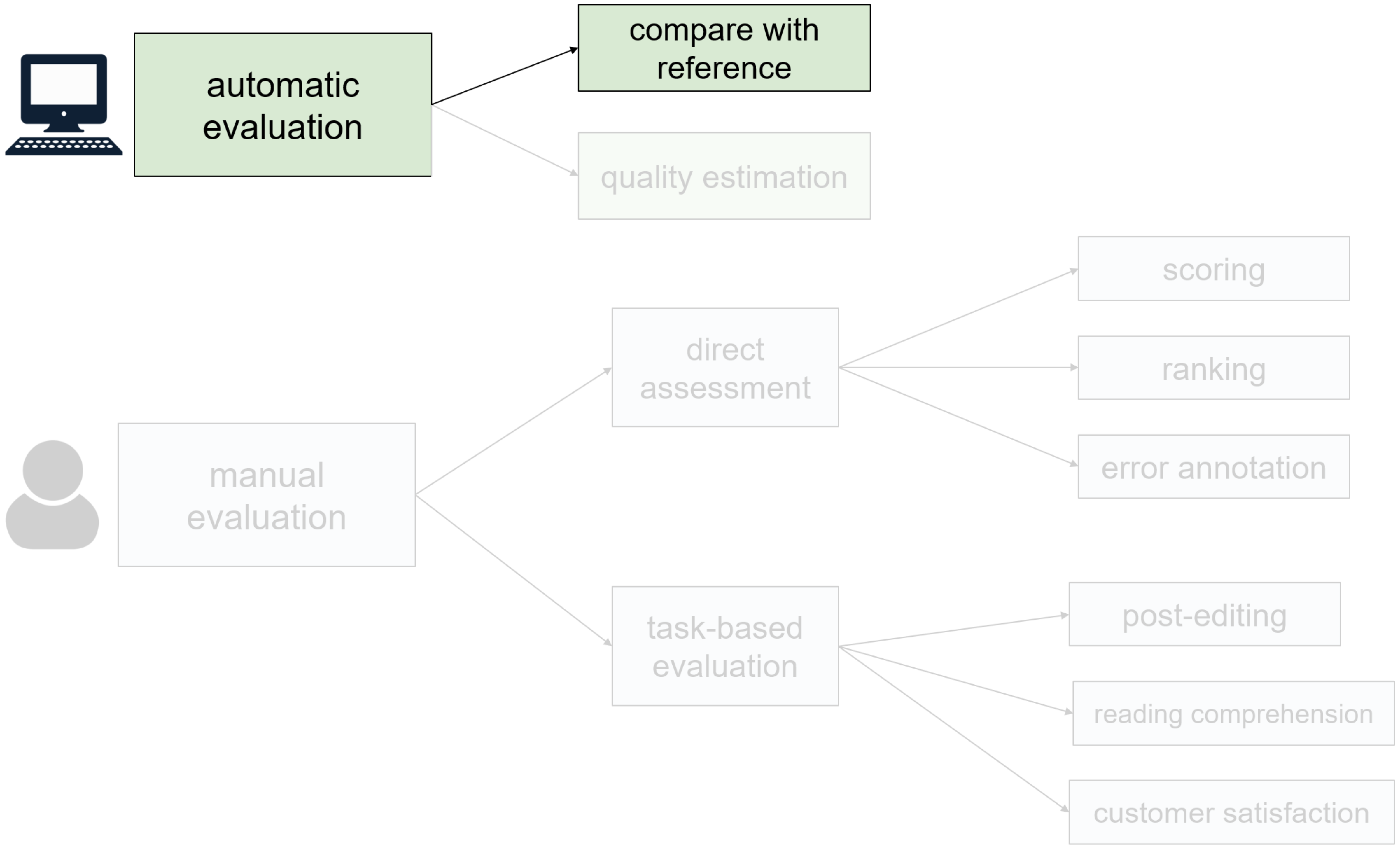
	Means	Task-specific?
• **MT Researchers**: • Rapid feedback for engineering. • Which setting is better? • Are differences significant?	Shallow surface comparison with one (!) reference translation	Intrinsic
• **Language Professionals**: • How many errors are in the MT? • What type/severity are they? • How difficult are they to post-edit?	Post-Editing, grading, error annotation, …	
• **(Potential) industrial MT users**: • What costs do I save when using this MT system? • How many cars will I sell in addition? • How many more customers can I serve?	Experiments with test users	Extrinsic

Evaluation approaches



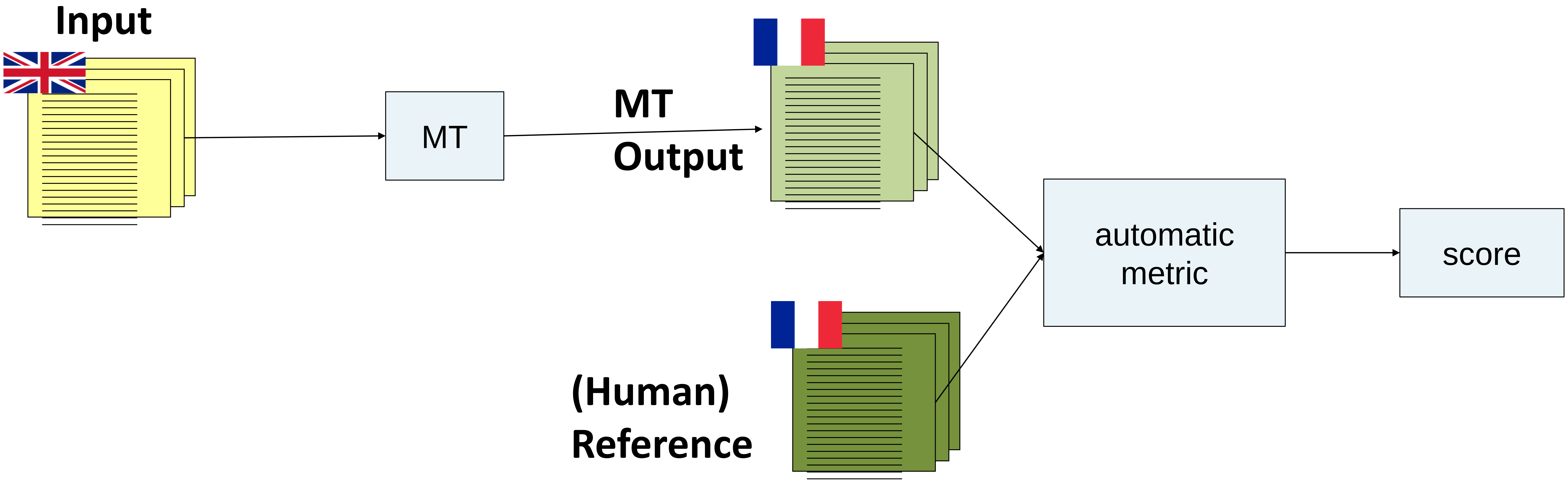
Source, Specia L. QT21 Project

Evaluation approaches



Source, Specia L. QT21 Project

Reference-based automatic metrics



The BLEU score

Geometric mean of modified precision scores of **overlapping ngrams** between translation and reference (1grams to 4grams)

- Brevity penalty to account missing words
- Calculated over an entire test-set
- The more the better
- Range between 0 and 100%,
  - 100% is very rare, humans and best systems score up to 70%
  - generic systems at ~35-40%.
- Useful to quickly compare systems, suffers in capturing complex grammar and morphology.

Reference: “Israeli officials are responsible for airport security”

MT Output: “[airport security] [Israeli officials are responsible]”

BLEU Metric:

1-gram precision: 6/6

2-gram precision: 4/5

3-gram precision: 2/4

4-gram precision: 1/3

Brevity penalty: 6/7

BLEU score = 52% (weighed geometric avg)

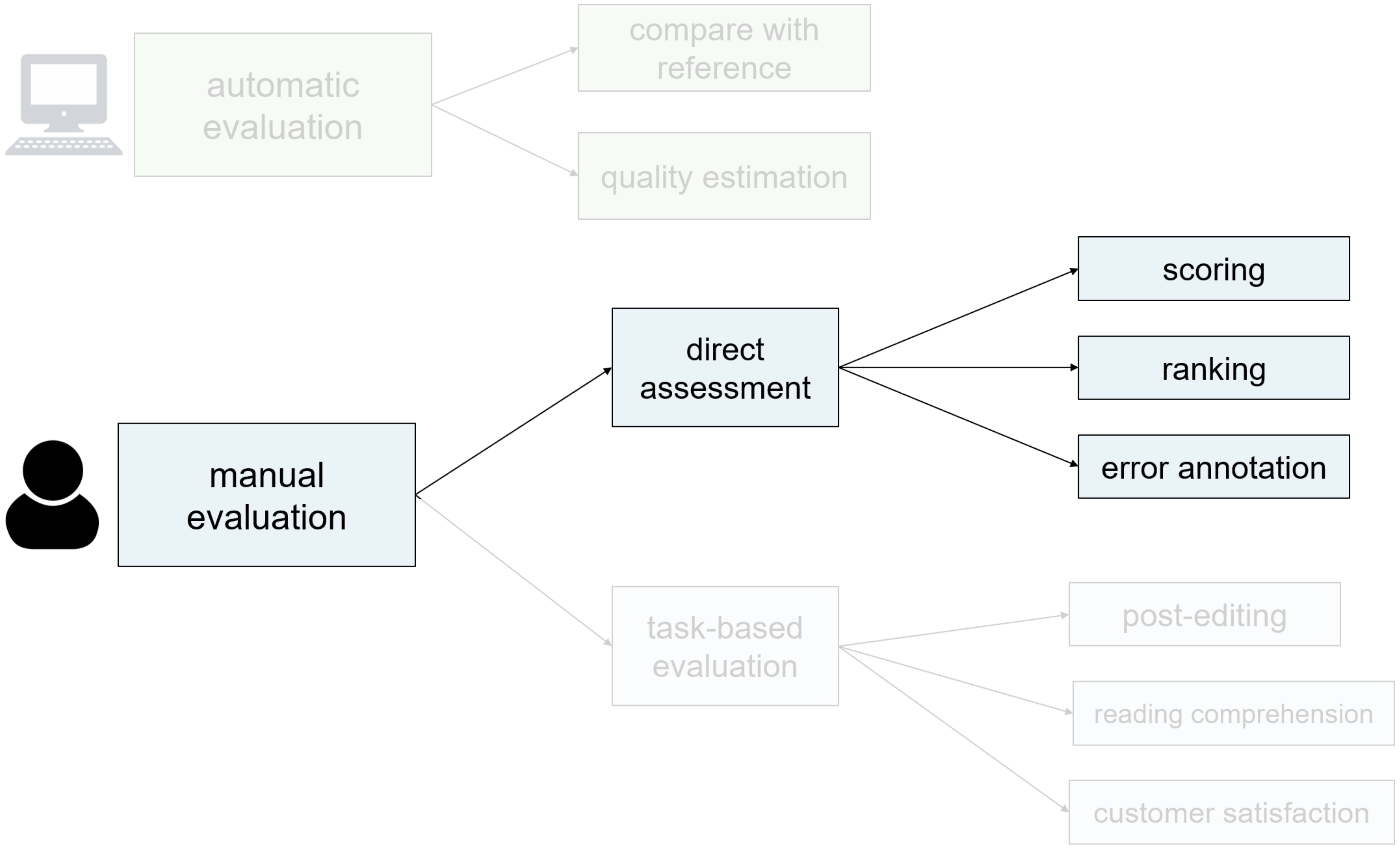
Improved Metrics: HTER, METEOR, BEER

Analytical approach:
benchmark sets for particular errors

	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	3386	6775	3700	3803	3635	8321

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

Evaluation approaches



Source, Specia L. QT21 Project

Human evaluation with direct assessment

Fluent speakers of the target language are asked to provide
a score on how good the translation is.

Read the text below. How much do you agree with the following statement:

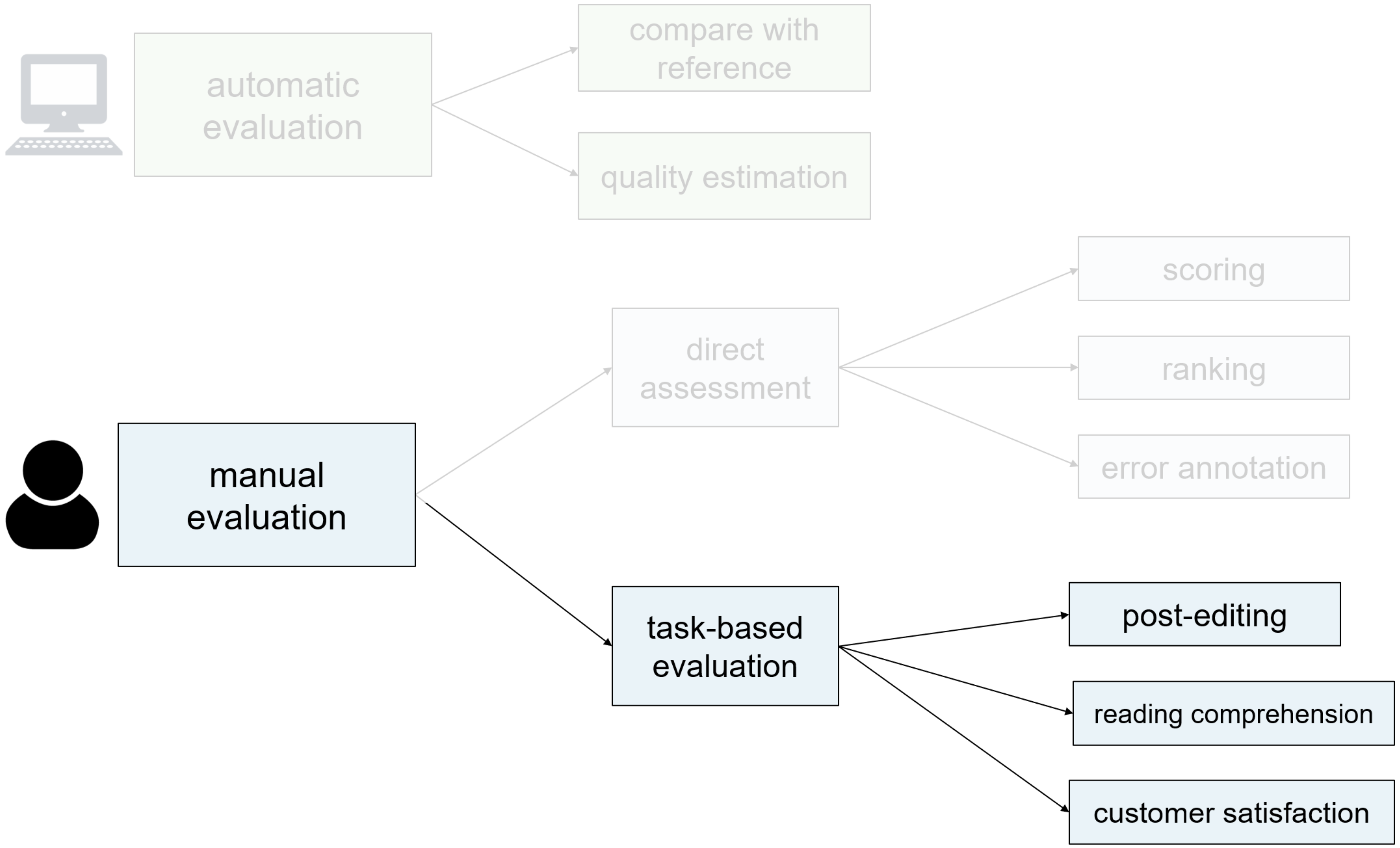
The black text adequately expresses the meaning of the gray text in English.

To snobs like me who declare that they'd rather play sports than watch them, it's hard to see the appeal of watching games rather than taking up a controller myself.

Snob like me, who say that it is better to be in sports than watching him, it is hard to understand the appeal of having to watch the game, rather than to take a joystick in hand.

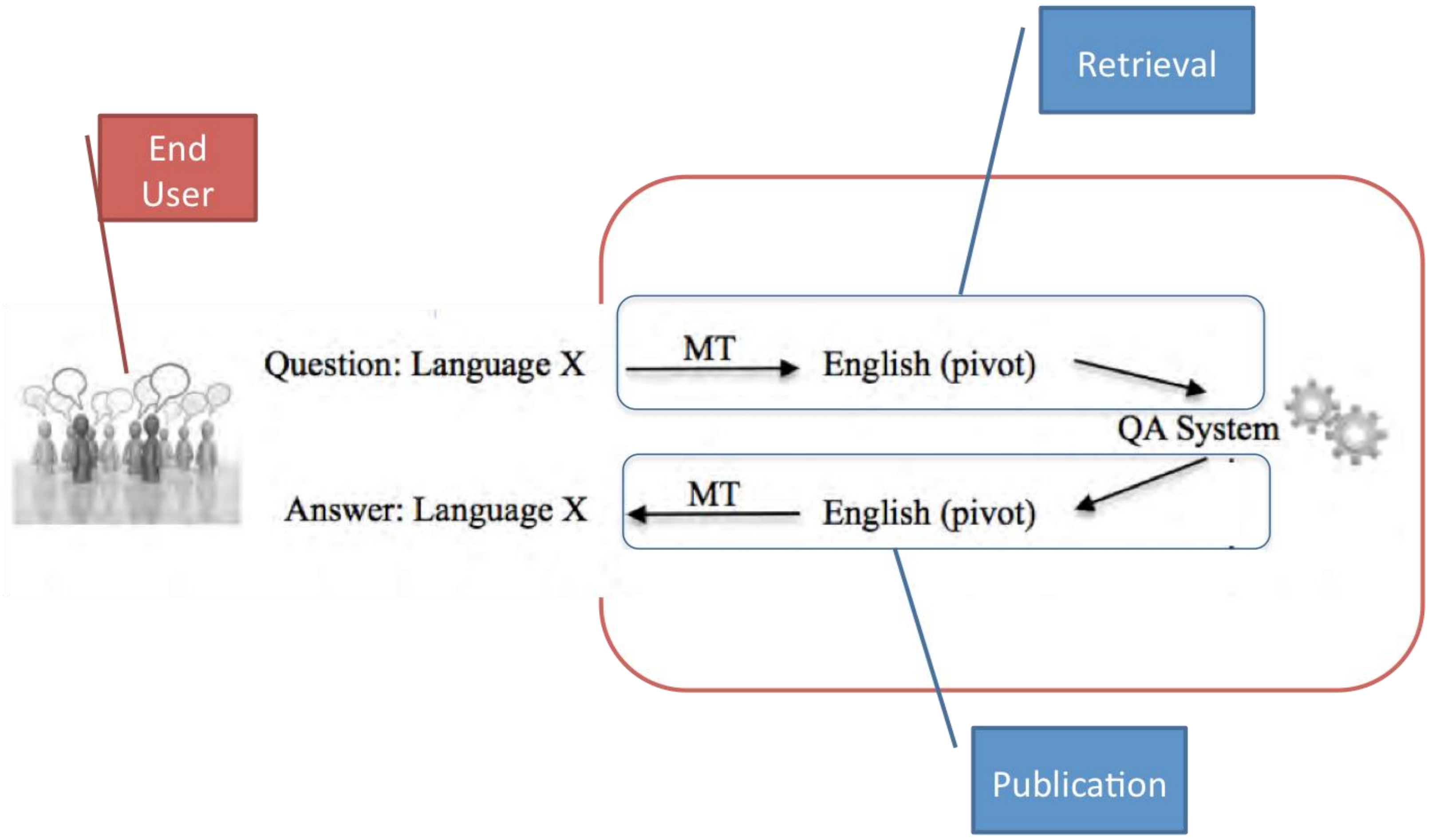
0 % 100 %

Evaluation approaches



Source, Specia L. QT21 Project

Task-based evaluation



	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**

Important papers for MT Evaluation

[1] Papineni et al., "BLEU: a method for automatic **evaluation** of machine translation", 2002 – *Definition paper for the automatic metric that everybody uses (and criticizes)*

[2] Hassan et. al., *"*Achieving Human Parity on Automatic Chinese to English News Translation*"* - 2018, *Controversial paper claiming that MT reached humans, lead to criticism by following papers such as:*

[3] Toral et. Al., "Attaining the Unattainable? Reassessing Claims of Human Parity in Neural Machine Translation" - 2018, *paper reassessing the conslusions of the previous*

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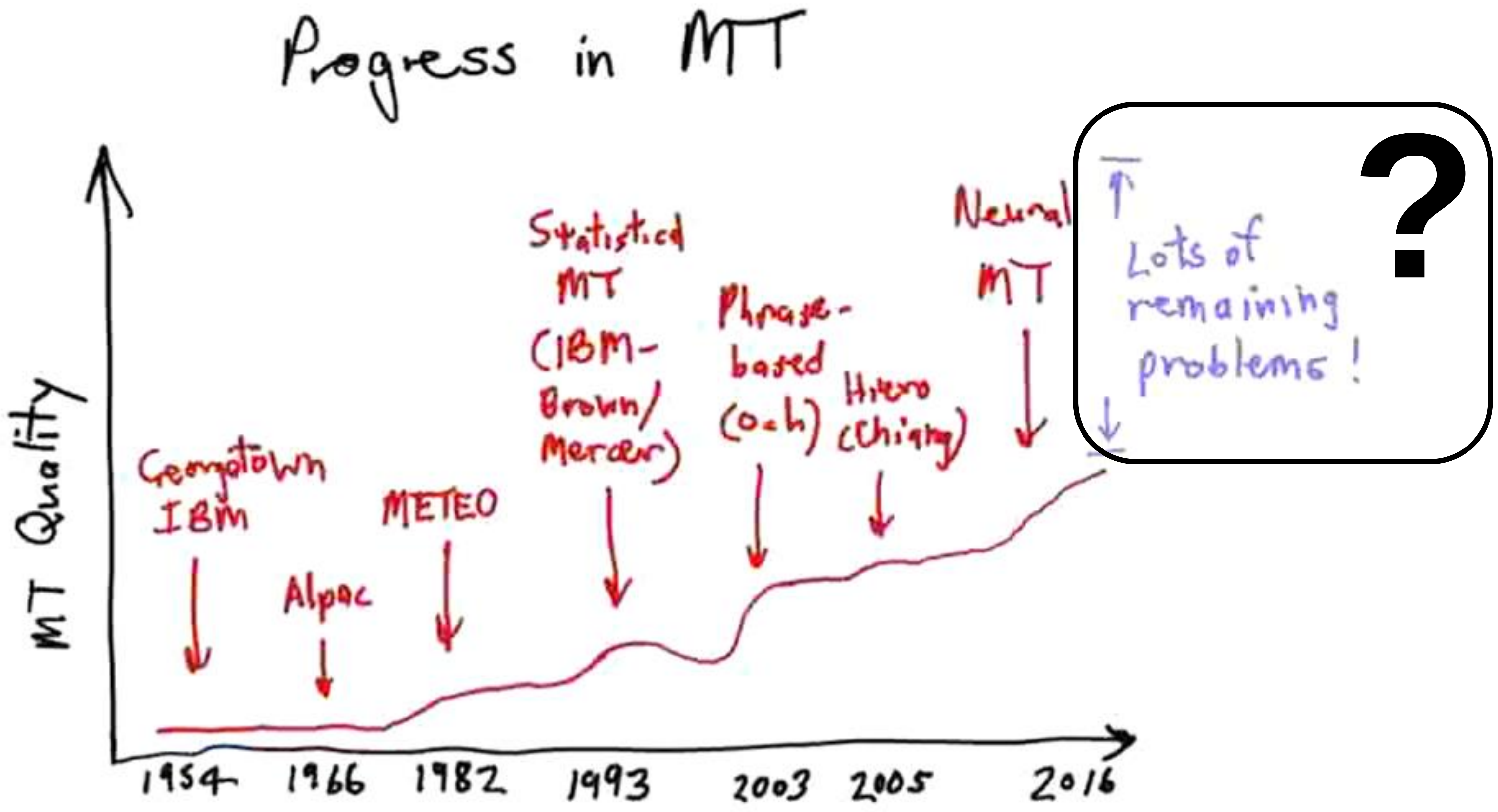
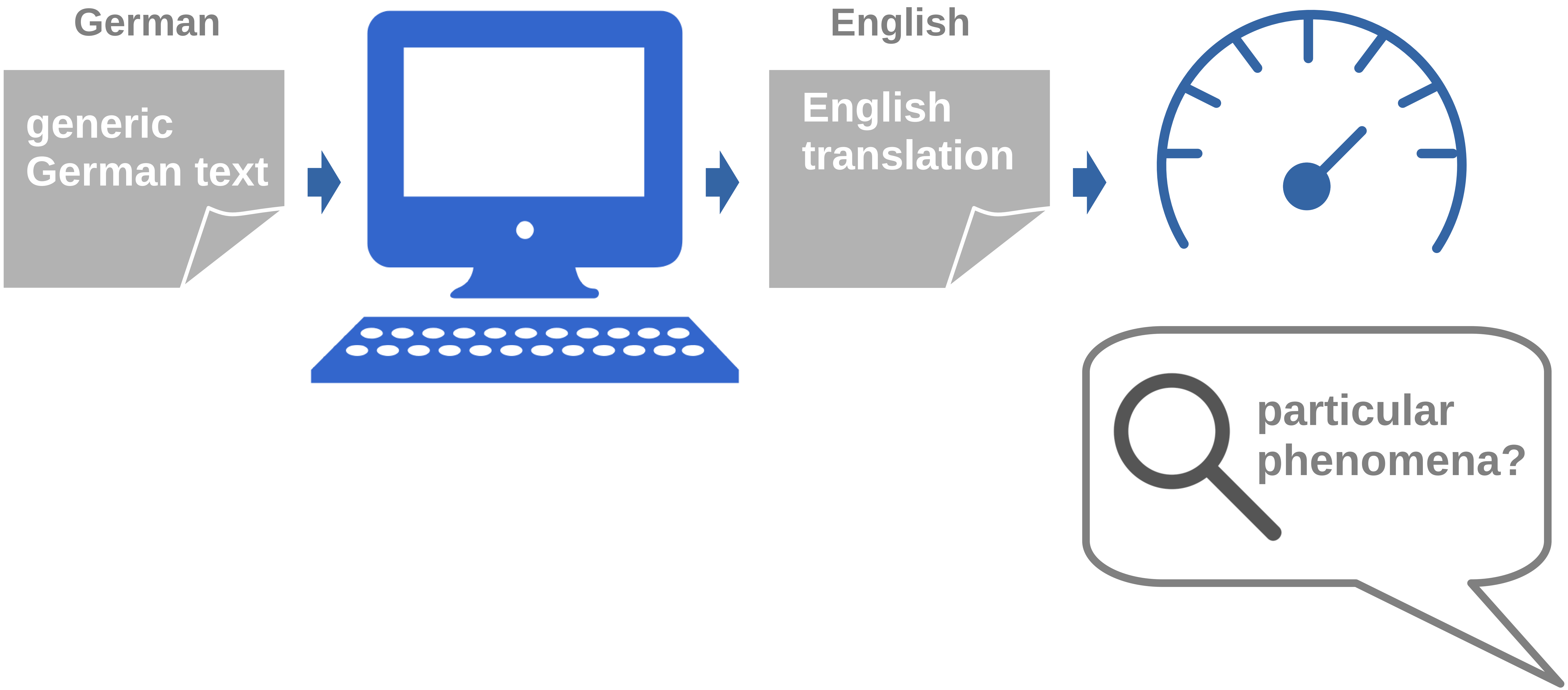
Are we close to human parity?



2016: Chris Manning: “**Lots of remaining problems**”

Evaluating overall system performance



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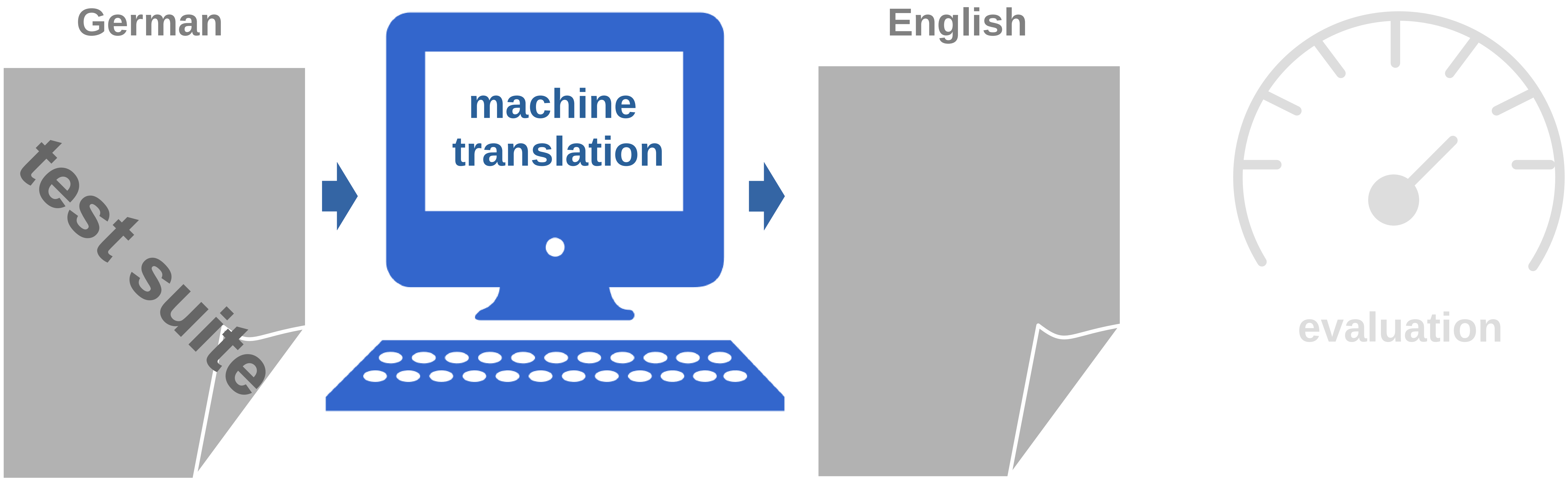
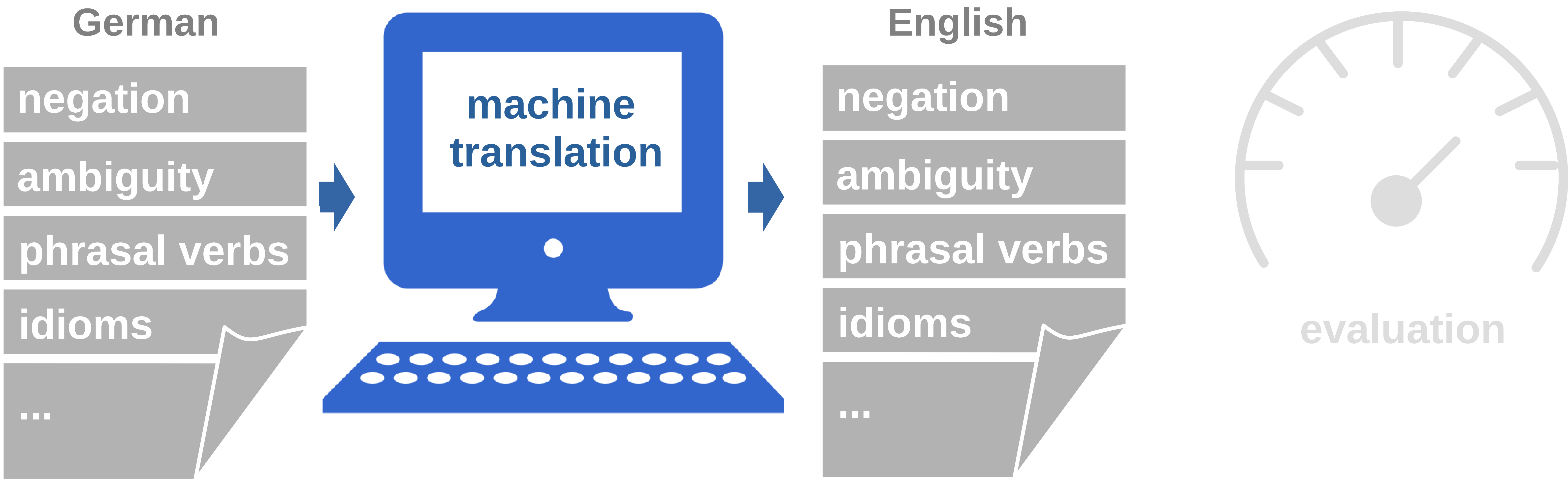


5.500 test sentences

translated test sentences

Evaluating overall system performance



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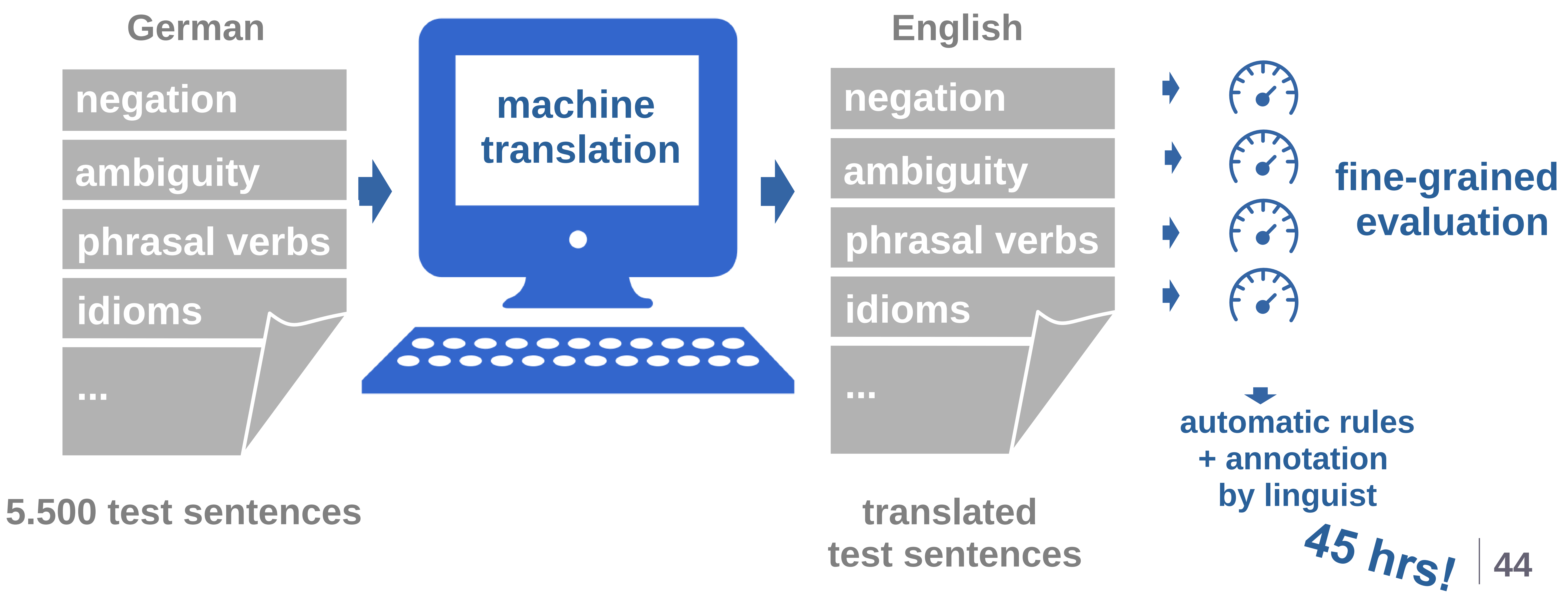
Evaluating overall system performance



107 phenomena

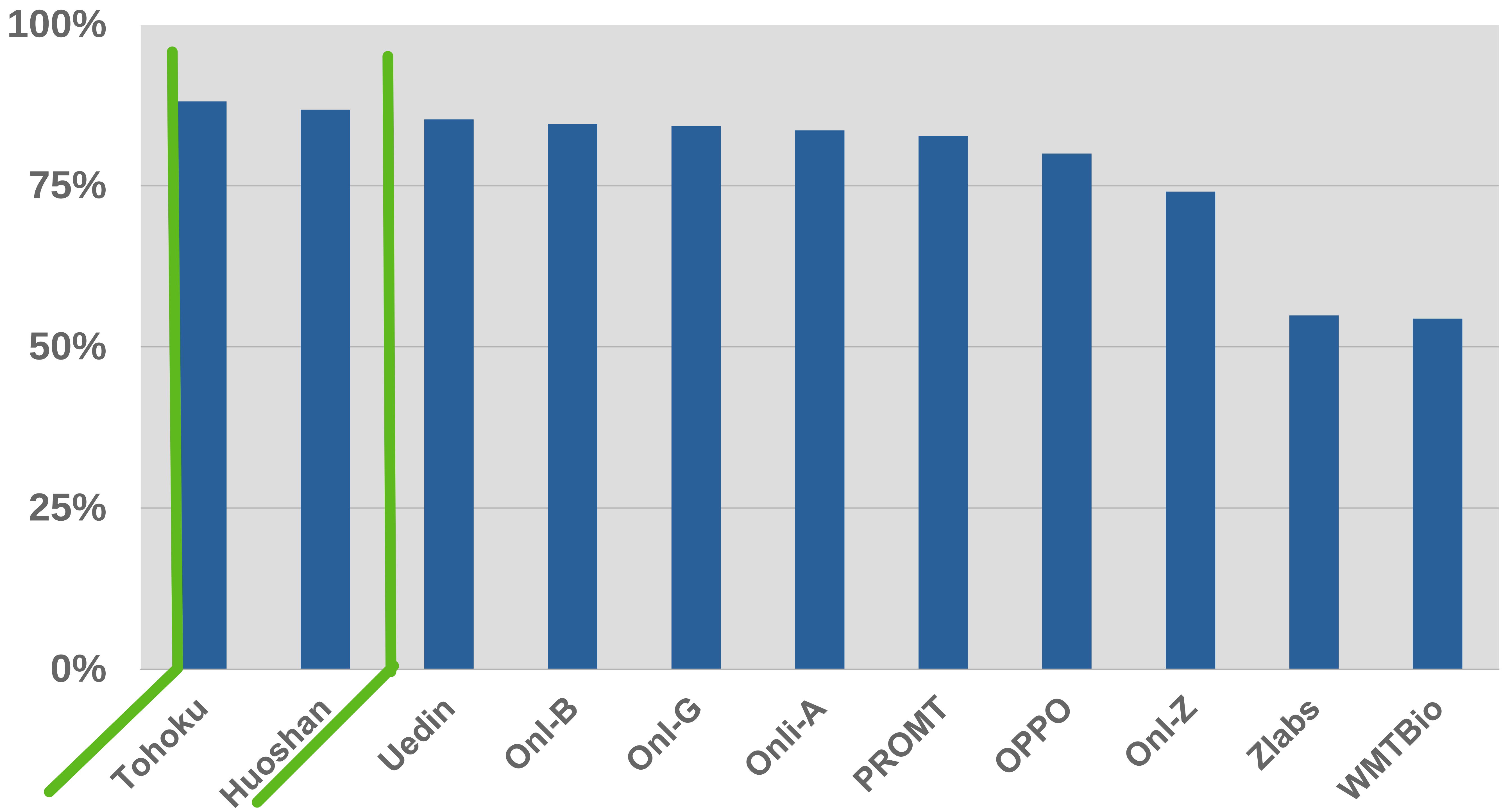
Lexical ambiguity	Prepositional MWE	Conditional	Modal - future I	Reflexive - pluperfect
Structural ambiguity	Verbal MWE	Ditransitive - future I	Modal - future I subjunctive II	Reflexive - pluperfect subjunctive II
Compound	Date	Ditransitive - future I subjunctive II	Modal - perfect	Reflexive - present
Phrasal verb	Domainspecific term	Ditransitive - future II	Modal - pluperfect	Reflexive - preterite
Gapping	Location	Ditransitive - future II subjunctive II	Modal - pluperfect subjunctive II	Reflexive - preterite subjunctive II
Right node raising	Measuring unit	Ditransitive - perfect	Modal - present	Transitive - future I
Sluicing	Proper name	Ditransitive - pluperfect	Modal - preterite	Transitive - future I subjunctive II
Stripping	Negation	Ditransitive - pluperfect subjunctive II	Modal - preterite subjunctive II	Transitive - future II
False friends	Coreference	Ditransitive - present	Modal negated - future I	Transitive - future II subjunctive II
Focus particle	External possessor	Ditransitive - preterite	Modal negated - future I subjunctive II	Transitive - perfect
Modal particle	Internal possessor	Ditransitive - preterite subjunctive II	Modal negated - perfect	Transitive - pluperfect
Question tag	Comma	Imperative	Modal negated - pluperfect	Transitive - pluperfect subjunctive II
Extended adjective construction	Quotation marks	Intransitive - fut**107 phenomena** ure I	Modal negated - pluperfect subjunctive II	Transitive - present
Extraposition	Adverbial clause	Intransitive - future I subjunctive II	Modal negated - present	Transitive - preterite
Multiple connectors	Cleft sentence	Intransitive - future II	Modal negated - preterite	Transitive - preterite subjunctive II
Pied-piping	Free relative clause	Intransitive - future II subjunctive II	Modal negated - preterite subjunctive II	Case government
Polar question	Indirect speech	Intransitive - perfect	Progressive	Mediopassive voice
Scrambling	Infinitive clause	Intransitive - pluperfect	Reflexive - future I	Passive voice
Topicalization	Object clause	Intransitive - pluperfect subjunctive II	Reflexive - future I subjunctive II	Resultative predicates
Wh-movement	Pseudo-cleft sentence	Intransitive - present	Reflexive - future II	
Collocation	Relative clause	Intransitive - preterite	Reflexive - future II subjunctive II	
Idiom	Subject clause	Intransitive - preterite subjunctive II	Reflexive - perfect	

107 phenomena

14 categories

- ambiguity
- composition
- coordination
- false friends
- long distance & interrog.
- multi-word ex
- named entity
- negation
- non-verbal agr
- function words
- punctuation
- subordination
- verb valency
- tense/mood

11 systems – WMT20 German-English



More about the Test Suite

[1] Pierre Isabelle, Colin Cherry, and George Foster. 2017a. A Challenge Set Approach to Evaluating Machine Translation. 2017

[2] Avramidis et. al, Linguistic evaluation of German-English Machine Translation using a Test Suite, 2019

Machine translation

1. Introduction
   - Definition and motivation
   - History and types
2. Neural machine translation models
   - RNN Encoder-decoder
   - Attention-based NMT
3. Advanced techniques
   - Subword units
   - Multilingual machine translation
   - Multimodal & speech translation
4. Evaluation
   - Purpose of evaluation
   - Users of evaluation
   - Evaluation approaches
5. Fine-grained evaluation
   - Test suites
6. Quality estimation
   - Feature-based model
   - Neural predictor-estimator
7. Sign language translation

Machine translation

input

Darüber soll am Anfang kommenden
Woche der Bundestag abstimmen.

system 1

This is to be voted on at the beginning of next week. | 0.7

system 2

The parliament is supposed to vote for it
beginning of next week | 0.9

system 3

About this voting should beginning next week | 0.3

reference

~~The parliament should vote for this
at the beginning of next week~~

Machine learning to predict scores of MT “quality”

- focus on one sentence at a time
- real-time use
(don't use reference)
- predict a metric of quality
(e.g. the human edit rate)

Various types of Quality Estimation

Linear / feature based model:

- analyze sentences with automatic tools
- generate numerical indicators of quality (features)
- use these to train a regressor/classifier given existing labels

(Blatz et. al, Specia et. al 2009)

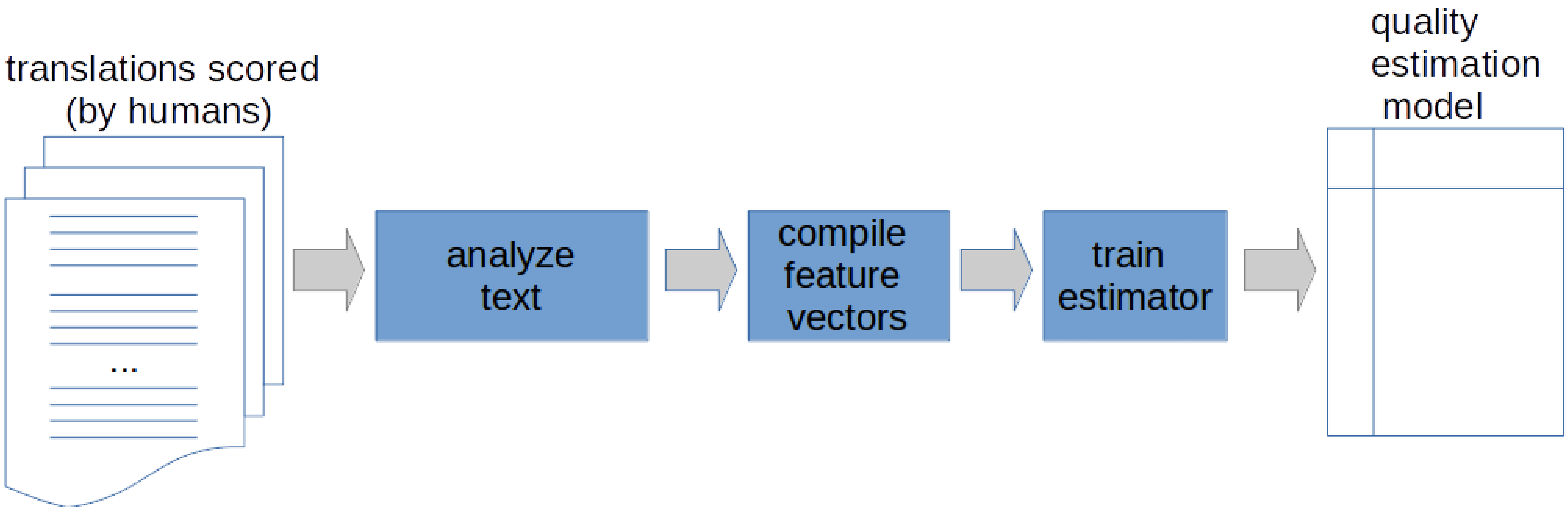
Neural:

- use neural models to perform automatic post-editing and score with the existing translation (Martins et. al 2017)
- train a joined “predictor-estimator” neural model (Kim et. al 2017)

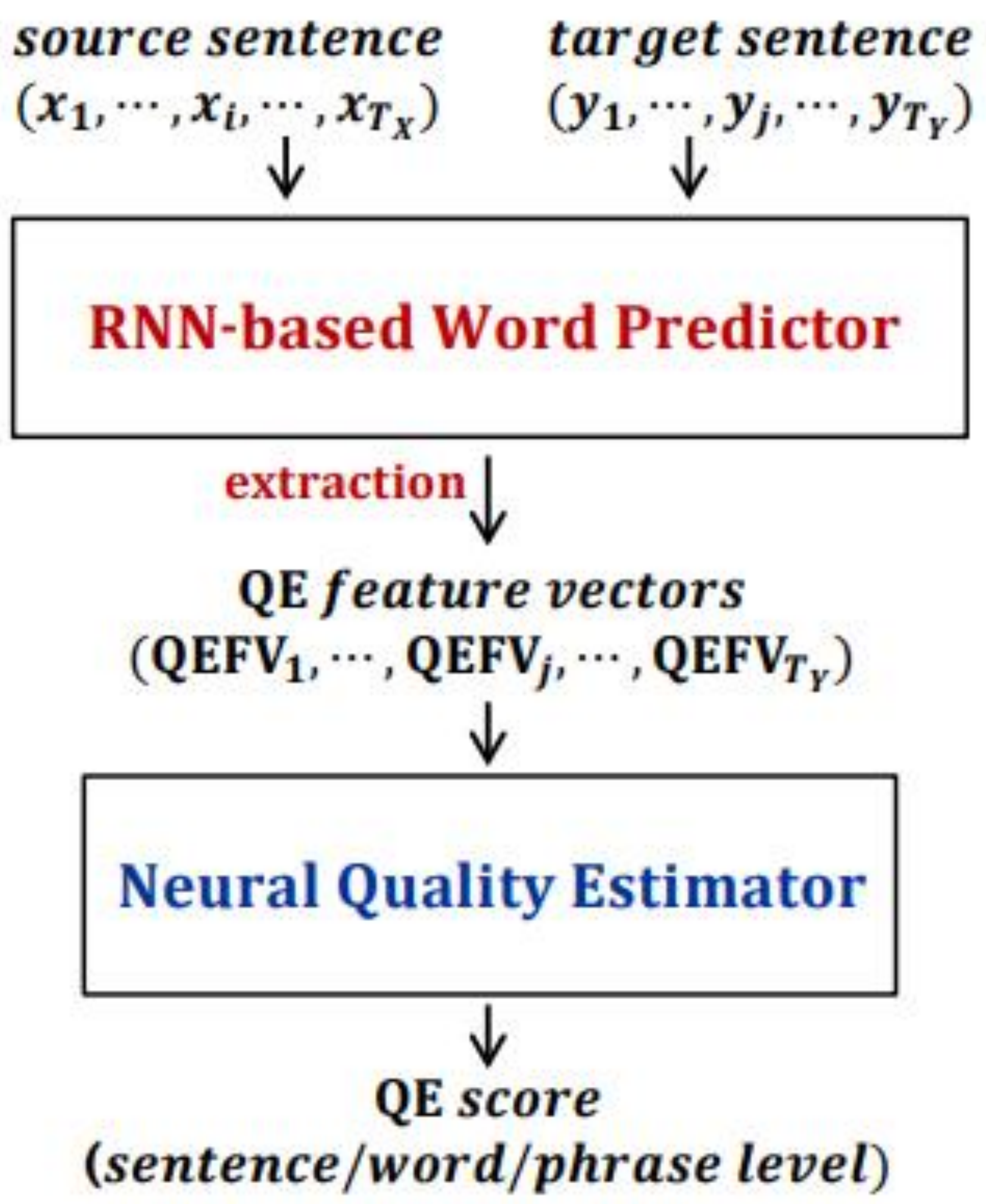
Challenge:

Systems are getting more efficient by the time, difficult to distinguish and predict machine translation errors

Linear, feature-based model



Predictor-estimator



Source: Kim et al., WMT2017

Machine translation

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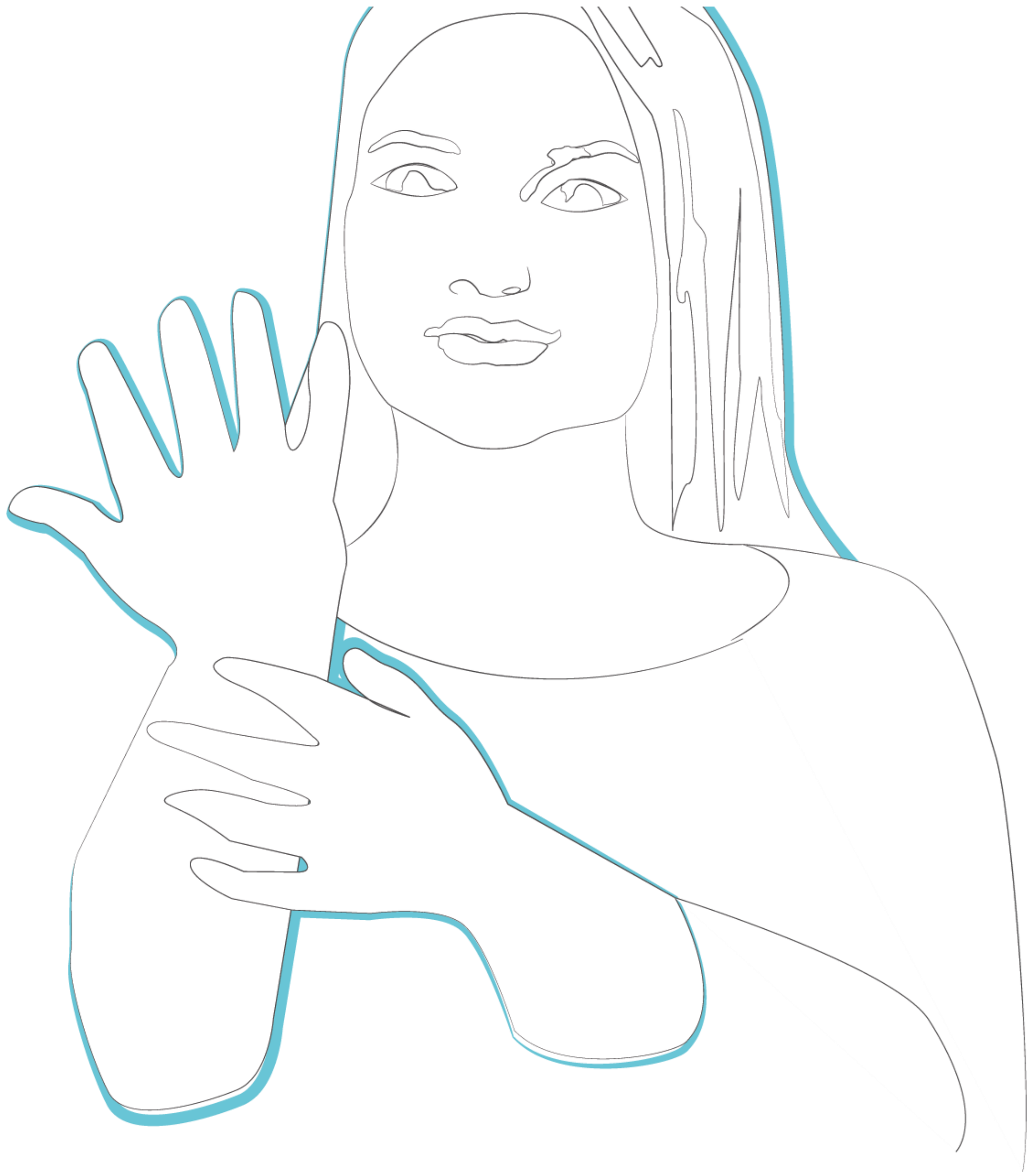
Sign Language

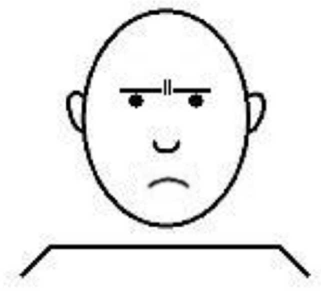


The sign language of the deaf is an independent visual language, which has been developed over the centuries in the everyday communication of deaf people.

Building blocks of sign language

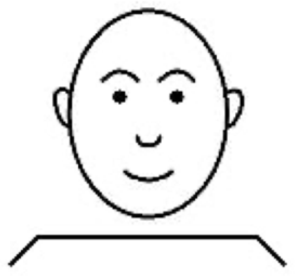
Papa

Herbst



Angst

(Faust schlägt an Brust)



Mut

(Faust schlägt an Brust)

a) manual

- hands (hand shape & hand position), arms
- executing position
- movement

b) non-manual

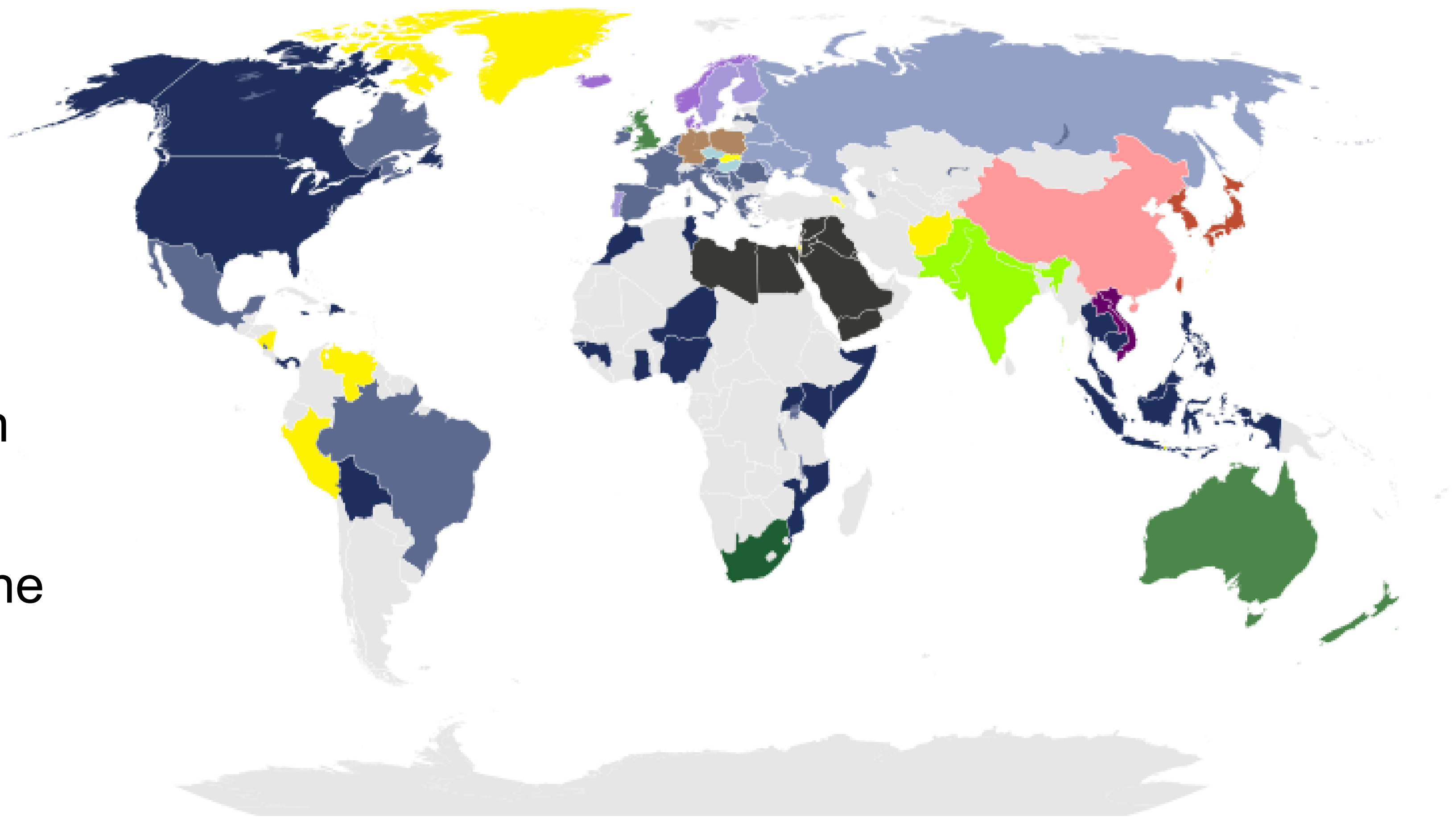
- facial expression (facial expression)
- direction of eyes
- head direction
- posture (especially of the upper body)
- Mouth image

Quick facts

- 0.1 % of the German population is deaf. This amounts to about 80.000 people.
- Every day 2 deaf children are born in Germany.

Sign languages around the world

- **Common misperception: all sign languages are the same. Nope!**
- ~130 national sign languages are known, while ~60 have been analytically processed
- American Sign Language (ASL) - different that the British or the Australian!



German sign language regional dialects
Berliner, Hamburger**,** Münchner, Frankfurter Dialekt Ruhrgebiet, etc. (~75% of vocabulary overlap)

Source: Horst Pagel Institut für Physiologie Universität zu Lübeck

Quick facts

- Sign language is equivalent to spoken language.
  - equally suitable to express meanings and feelings
  - possible to express and discuss complex matters
  - it consists of a comprehensive vocabulary and an elaborate grammar.
- not invented by a person or institution (like for example esperanto), but was continuously and organically developed by its native speakers.

- Not limited to visible things, that can be visualized with hand signs and gestures.
- Signs have a complex substructure, that can be analytically represented by rules that connect the **shape of the hand, orientation of the hand, position relative to the body and motion.**

History of automatic sign language translation

1977: Research project successfully matched English letters from a keyboard to ASL manual alphabet letters which were simulated on a robotic hand.

1996: Recognition method with gloves (only 20 gestures) and (shallow) neural networks

2005: Recognition method using cameras was proposed (but not implemented)

2012: First work on (Chinese) sign language translation with Kinekt (still low accuracy)

2016: First system using deep learning to recognize gestures on videos (but does not yet produce text)

2018: First end-to-end system using techniques similar to text Machine Translation (but only trained on weather forecasts!)

From text to signing avatar

This is the text for generating sign language gestures using animation

→ **Machine learning-based transcription** → **animation** →

Image source: babysignlanguage.com

From sign language to text

camera and/or wearables

machine learning

This is the text that resulted from the decoding of the sign language gestures using motion detection gloves through a deep learning framework

text / speech

Image source: babysignlanguage.com

Different granularities: Finger alphabet

Isolated sign language translation

Isolated sign language translation

Isolated sign language translation

Continuous sign language translation

video

UNIVER SITY1	HERE1	GERMA N1*	GOOD3
uni	[MG]	de{utschl and}	[MG]

glosses

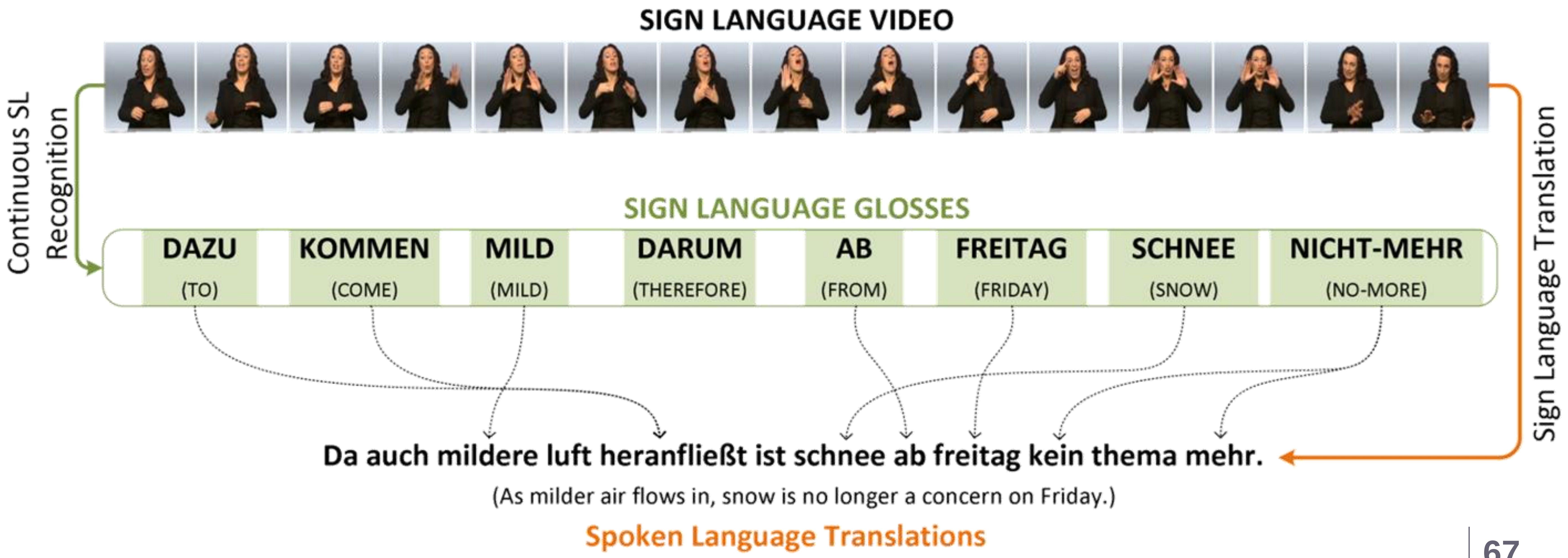
Universities here in Germany are good

text / speech

Sign language recognition

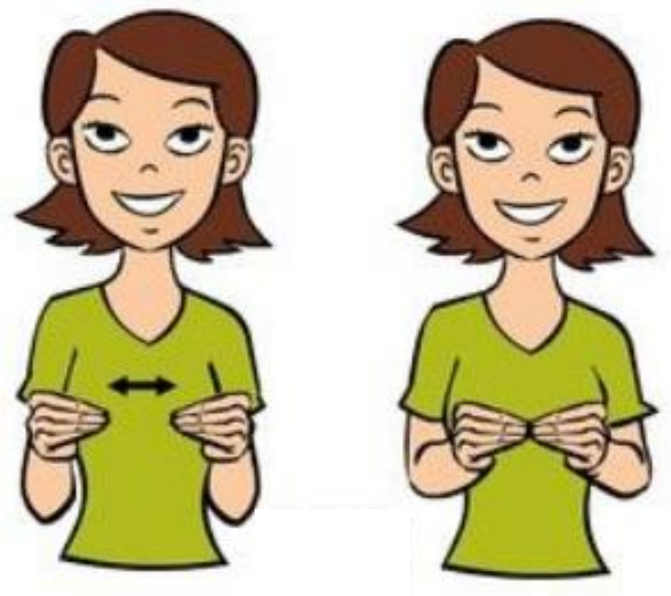
Sign language translation

Continuous sign language translation

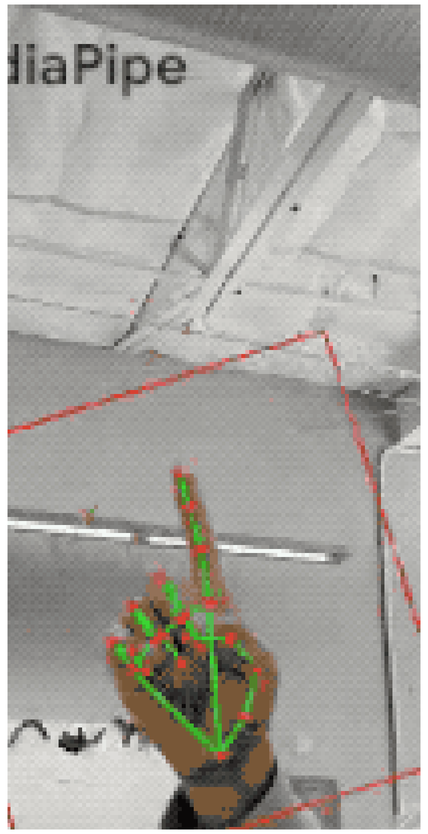


Source: Camgoz et. al, “Neural Sign Language Translation”, RWTH 2019

Sign language recognition via body recognition



video



Analyze positions for body “landmarks”

First finger coordinate:
(170,100)→(100,-10)
Palm rotation: -100°
Wrist movement:
(180,30)→(80,190)
...

Numerical values for body landmarks

UNIVE RSITY1	HERE1	GERM AN1*	GOOD 3
uni	[MG]	de{utsc hland}	[MG]

glosses