Outbound Translation User Interface Ptakopět: A Pilot Study

Vilém Zouhar, Ondřej Bojar
Charles University
Prague, Czech Republic
{zouhar, bojar}@ufal.mff.cuni.cz

Abstract

It is not uncommon for Internet users to have to produce text in a foreign language they have very little knowledge of and are unable to verify the translation quality. We call the task "outbound translation" and explore it by introducing an open-source modular system Ptakopět. Its main purpose is to inspect human interaction with MT systems enhanced with additional subsystems, such as backward translation and quality estimation. We follow up with an experiment on (Czech) human annotators tasked to produce questions in a language they do not speak (German), with the help of Ptakopět. We focus on three real-world use cases (communication with IT support, describing administrative issues and asking encyclopedic questions) from which we gain insight into different strategies users take when faced with outbound translation tasks. Round trip translation is known to be unreliable for evaluating MT systems but our experimental evaluation documents that it works very well for users, at least on MT systems of mid-range quality.

Keywords: Quality Estimation, Machine Translation, Outbound Translation

1. Introduction

For most language pairs, machine translation (MT) quality is limited. Yet MT in everyday use greatly helps by providing low quality, preview translation also called gisting. The complement of gisting is outbound translation. In both cases, a message is transferred between the author and the recipient and each of them has a sufficient knowledge of only their language. In outbound translation, the author is responsible for creating correct messages in the recipient's language. In gisting, the message is sent in the author's language and the responsibility to correctly interpret it lies on the recipient. An example of gisting would be browsing on a website in a foreign language, whilst filling in a form in a foreign language would be an example of outbound translation.

When translating to foreign languages, users cooperate with machine translation tools to produce the best result. Machine translation can prepare a first version of the text, or it can be used to verify the user's own translation to some extent.

Users translating to languages, which they do not master enough to validate the translation, need some additional system for verification and assurance, that the machine translation output is valid. For this, Ptakopět offers word-level quality estimation (QE), simulated source complexity and backward translation. While round trip translation may be unreliable for fully automatic evaluation of MT quality (Somers, 2005), it is still a very common strategy for users.

The paper is structured as follows: We briefly introduce the components we rely on in Section 2. and describe Ptakopět in Section 3., including the underlying models. The experiment setup is presented in Section 4. and the results in Section 5. We conclude in Section 6.

All gathered data is stored in a public repository.[1]

[1] https://github.com/zouharvi/ptakopet

2. Background

2.1. Quality estimation

Machine translation quality estimation is used mostly in translation companies to minimize post-editing costs. Unfortunately, quality estimation cues are missing in most of the mainstream public translation services, such as Google Translate[2] (provides alternatives to words), Microsoft Translator[3] or DeepL[4] (provides alternatives to phrases).

Quality estimation is usually performed on bitext (parallel text composed of source and target language versions). The four levels with the following metrics, as distinguished by the WMT shared task[5] are:

- **word-level** – words in a target sentence are classified as OK or BAD
- **phrase-level** – phrases in a target sentence are classified as OK or BAD
- **sentence-level** – target sentence receives a score, such as percentage of edits needed to be fixed: HTER, post-editing time in seconds, or counts of various types of keystrokes.
- **document-level** - target document gets an MQM score[6]

For our case, only word or phrase-level quality estimates are sufficiently informative.

2.2. Word Alignment

Word alignment is the task of matching two groups of words in a sentence pair if and only if they are each other's translations. Word alignment usually follows after sentence alignment. An example of word alignment between an English sentence and translated German sentence can be seen in Figure 1.

[2] translate.google.com
[3] bing.com/translator
[4] deepl.com/en/translator
[5] statmt.org/wmt19/qe-task.html
[6] qt21.eu/mqm-definition/definition-2015-12-30.html

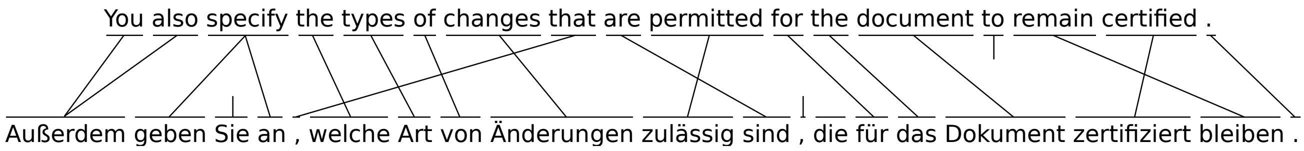

Figure 1: Word alignment of the first sentence in WMT17 shared task 2 training data (English to German)

Word alignment in Ptakopět is used to tell users which parts of their source sentences were probably translated badly. In the context of outbound translation, highlighting parts of the translated sentence provides only little information to the user, since they do not know what do they map to in the source sentence.
Ptakopět highlights words in the source sentence with the same intensity as the matching words in the target sentence. The same form of assistance could also be provided directly using some form of a source complexity estimator instead of the combination of quality estimation and word alignment.

3. Ptakopět

Ptakopět is a modular system implemented primarily in TypeScript (frontend) and Python (backend), interfacing external text processing components using web sockets or Unix pipes.
Section 3.1. introduces the frontend-backend structure of Ptakopět. Section 3.2. illustrates the current user interface. We then describe the particular MT system chosen for our experiment (Section 3.3.), the quality estimation models and training data for our language pair of interest (Section 3.4.)

3.1. Backend and Frontend

The Ptakopět backend[7] is a simple server with a queue, that responds to quality estimation and word alignment requests. Apart from that, it serves as a logger endpoint for experiments. The Ptakopět frontend[8] is a web page[9], which allows the users to translate text with the help of quality estimation (highlighting badly translated words) and backward translation. It was designed so that more components can be added and different approaches tried.
Both the server and the frontend can be run and installed locally. Technical details with instructions are in the online documentation.[10]

3.2. User interface

The main Ptakopět layout is displayed in Figure 2. It contains three text areas. The top-most is the input field for text in the source language. Underneath follows translation to the foreign language and bottom-most is the backward translation. Quality estimation is performed on the text between the first and the second input fields (source and forward translation) and is rendered in the latter. Quality estimation is then transferred via word alignment to the source text.

[7]github.com/zouharvi/ptakopet-server
[8]github.com/zouharvi/ptakopet
[9]ptakopet.vilda.net
[10]ptakopet.vilda.net/docs

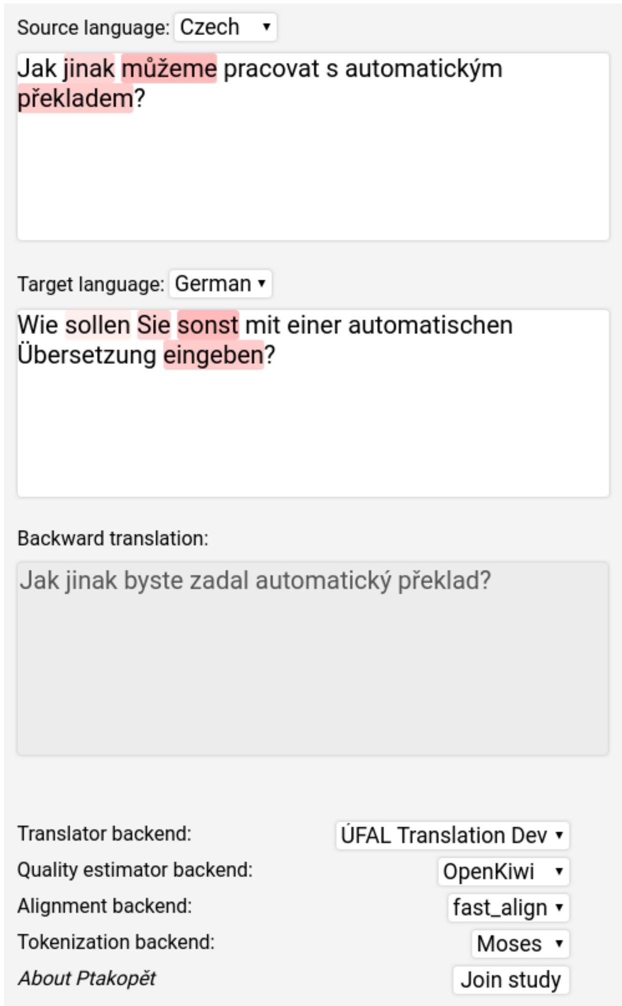

Figure 2: Example sentence in Ptakopět with quality estimation highlighting and backward translation

The highlighting of translated word quality is being done using a plugin by Will Boyd[11] and it was altered for Ptakopět.[12]

3.3. Machine translation models

Ptakopět is flexible in terms of the underlying MT engine and even allows the user to choose the engine on the fly with a drop-down menu. For the purposes of our experiment, we stick to one particular engine of mid-range translation quality. We motivate the choice by the fact that very high-quality MT is available only for a handful of language pairs and these language pairs may not need any support in outbound translation.

[11]github.com/lonekorean/highlight-within-textarea
[12]github.com/zouharvi/highlight-within-textarea

CS (MT): použijte dialogové okno Vlastnosti videa ke změně vlastností videa pro video soubory FLV .

EN: use the Video Properties dialog box to change video properties for FLV Video files .

DE (MT): im Dialogfeld " Videohäuser " können Sie Videoeigenschaften für Flv Video-Dateien ändern .

QE: OK OK OK OK OK OK OK OK OK BAD BAD OK OK

Figure 3: Quality estimation tags for tokens and gaps on German sentence translated from English (from WMT19 quality estimation shared task) together with synthetic Czech source (translated from English). MT systems are independent.

We made use of two neural MT Transformer models (CS→DE and DE→CS) described in Section 7 in (Kvapilíková et al., 2019). They were trained on 8.8M Czech-German sentence pairs for 8 days from scratch until convergence.

For performance sake, the system accepts only a limited number of subword units per translation computation. Most sentences fit into this limit, but longer sentences do not, which results in context loss.

Generally, both MT models made obvious mistakes occasionally, such as adding extra words.

3.4. Quality estimation models

Ptakopět uses quality estimation for highlighting badly translated words. There were three available implementations but none of them was suitable for online use out of the box. We also synthesized QE training data for our language pair of interest, see Section 3.4.4.

3.4.1. QuEst++

The main pipeline of QuEst++ (Specia et al., 2015) consists of feature extraction and machine learning prediction. It first extracts features WMT12-13-14-17[13] from the input data, such as POS, indication of words' presence in a dictionary and word length and then runs a standard ML algorithm e. g. Cross-validated Lasso, using the LARS algorithm. Especially the feature extraction part is not optimized and it is quite slow.

The original feature extractor system supports English-Spanish quality estimation. We experimented with feeding it English-Czech quality estimation data and expected that the ML part would disregard noisy or low information features caused by feeding the feature extractor unsupported language. We found that the performance regressed so considerably, that we did not experiment further with Czech-German quality estimation in QuEst++.

3.4.2. DeepQuest

DeepQuest (Ive et al., 2018) takes a neural approach to quality estimation and is capable of performing well on any language pair. The toolkit offers two architectures: a reimplementation of Predictor-Estimator architecture (Kim et al., 2017) and a bidirectional recurrent neural network (bRNN) system. DeepQuest offers document-level, sentence-level, phrase-level and word-level quality estimation.

We trained the bRNN model on WMT17 English-German data and synthesized WMT17 Czech-German data described below. This architecture does not require pretraining, is less complex and provides results close to Predictor-Estimator (Ive et al., 2018).

3.4.3. OpenKiwi

OpenKiwi (Kepler et al., 2019) implements three quality estimation models: QUality Estimation from ScraTCH (Kreutzer et al., 2015), NuQE (Martins et al., 2016) used for WMT19[14] baseline and Predictor-Estimator (Kim et al., 2017). Additionally, OpenKiwi implements stacked ensembling as proposed by Martins et al. (2017).

We opted for the Predictor-Estimator architecture for our experiment, because even though it requires pretraining, it does not consume so many resources compared to the stacked ensemble. This architecture also provides the best results in comparison with other architectures without ensembling as shown in (Kepler et al., 2019).

OpenKiwi, in general, proved to be faster, more robust and easier to use than DeepQuest. Because of this, the experiment was conducted with OpenKiwi quality estimation backend.

3.4.4. Czech-German Quality Estimation Dataset

Since relevant Czech-German training data for QE were not available, we synthesized them from WMT 2017 English-German Word Level Quality Estimation dataset in the IT domain (Specia and Logacheva, 2017). Such data are composed of source language sentences (EN), target language sentences (DE) and OK/BAD tags for each word (QE).

We processed the WMT17 English-German data to obtain Czech-German data by translating the source language sentences using LINDAT Translation (Popel, 2018) from English to Czech. Given triplets (EN, DE, QE), we thus create triplets of (CS, DE, QE). An example of this can be seen in Figure 3.

To make sure the data did not lose quality, we performed the following experiment: We manually annotated 30 Czech-German and 20 English-German sentences for word-level quality estimation, in the same format as the original English-German dataset, i.e. labelling German words with OK/BAD labels given the source sentence. The original English-German annotation served as the golden standard. Our annotation for English-German was created independently of it and it served as a benchmark for our agreement with the original.

Table 1 shows the confusion matrices of our annotations compared to the golden standard. The distributions for both language pairs are similar. The sample is very small and the sets of underlying sentences (20 English and 30 Czech)

[13] quest.dcs.shef.ac.uk/quest_files/features_blackbox_baseline_17

[14] statmt.org/wmt19/qe-task.html

All	
TP=74.57%	FP=2.68%
FN=12.98%	TN=9.76%
Czech-German	
TP=77.58%	FP=3.68%
FN=11.03%	TN=7.71%
English-German	
TP=69.81%	FP=1.11%
FN=16.07%	TN=13.02%

Table 1: Confusion matricies for word level quality estimation annotations of Czech-German and English-German.

had to be different because the annotation was carried out by a single person, but the results nevertheless indicate that this transfer of QE data by machine-translating the source is viable. The similarity of confusion scores can mean one of the following. Either the German sentence itself was representative enough for the annotator to produce classes with similar distributions, or that both the English and the Czech sentences provided the same level information. In both cases, the pairs (EN, DE) and (CS, DE) seem equally usable which means that we should be able to train similarly good quality estimation model based on the synthetic Czech source.

3.5. Alignment

We use Hunalign (Varga et al., 2007) for sentence alignment and fast align (Dyer et al., 2013) for word alignment, both because of their ease of use and performance.

Both sentence and word alignment systems are unsupervised, operating only on the given input data. Because the real input received by Ptakopět is generally very short, we always mix it with a baseline parallel corpus. This increases the vocabulary coverage for word alignment and improves stability of sentence alignment.

The training data for quality estimation (Section 3.4.4.) already limited us to the IT domain. We thus choose a similar domain also for this additional corpus for alignment, the widely available Ubuntu 14.10 parallel corpora (Tiedemann, 2012). Specifically, we use parallel corpora for the following language pairs: EN-CS (6492 sentence pairs), DE-CS (6604 sentence pairs), DE-EN (13245 sentence pairs), CS-FR (6603 sentence pairs), EN-FR (9375 sentence pairs). These corpora are used both for word and sentence alignment.

4. Experiment Setup

The goal of our pilot experiment was to observe and describe strategies users take when tasked to do outbound translation and see if and how Ptakopět helps in the task.

The experiment was carried out remotely, in two phases. In the first phase, annotators were presented with a sequence of web pages and asked to produce a German sentence given a stimulus at each of them. In the second phase (Section 5.4.), a highly-skilled speaker of German validated the outputs of the first phase.

QE highlighting in Ptakopět was enabled only for the first section, because the QE model did not perform well on out of domain sentences.

4.1. Annotators

There were 8 annotators in total, divided into two groups. The first one was composed of 4 people without advanced knowledge of English[15] and the second one consisted of 4 people with English level of at least C1 on the CEFR scale. All of the annotators had German knowledge of at most A1. We refer to these groups as bilingual and monolingual respectively.

4.2. Data

For our experiment, we gathered input data and prompted users to reformulate a specific question or work with the text in some way. Each data section was meant to correspond to some real-life applications.

4.2.1. Seeking help in technical issues

For the best match with the QE training data (Section 3.4.4.), we extracted 35 stimuli (in Czech) from WMT 2017 English-German quality estimation dataset. The sentences describe technical issues when using common office or desktop publishing programs.

The annotators were expected to translate the description of the issue to German relying on machine translation and quality estimation tools. Furthermore, we think that explaining technical issues to IT support in an unknown language is a common outbound translation use case. An example of a technical issue is in Figure 4 (translated to English).

Issue description:
The date format cannot be changed from Month-Day-Year to Day-Month-Year.

Figure 4: Example description of a technical issue from the experiment dataset.

4.2.2. Common administrative issues

The next 30 test pages in the experiments provided a source text in Czech with a piece of factual information (a short span in the text) highlighted. The annotators were supposed to formulate questions that ask for this factual information. This data was collected from the instructions on how to proceed in various administrative topics at the Municipal District of Prague 6[16]. This use case is inspired by the day to day problems of citizens living in a foreign city. With the help of MT, they can get the gist of regulation or relevant document but they may need to ask the administration for some clarification or a specific detail.

An example of an administrative issue stimulus can be seen in Figure 5. For presentation purposes, we again translate the stimulus into English but the annotators saw Czech text and were expected to formulate the question in Czech so that MT produces a good German version.

[15] Note that the annotators never needed to produce any English text in the experiment. Only one subset of the test data needed English comprehension.

[16] praha6.cz/codelat/index.php

Paragraph with span:
Applicant pays 100 CZK when changing a surname that is derogatory, eccentric, ridiculous, garbled or foreign.

Figure 5: Example administrative topic and the factual information to ask for (the price) highlighted

4.2.3. Encyclopedic knowledge: SQuAD 2.0

The last section of the experimental data was based on the Stanford Question Answering Dataset 2.0 (Rajpurkar et al., 2018) and its (machine-translated) Czech version. The basic unit of SQuAD are paragraphs with spans. In the context of SQuAD 2.0, this means that there already existed a question for this span. In our experiment, we disregard the existing questions and ask our annotators to ask for the highlighted information again. We are thus creating additional questions for the SQuAD dataset, now in Czech.
An example of a paragraph from SQuAD 2.0 and questions we collected from the Ptakopět pilot study (again translated to English) can be seen in Figure 6.

Paragraph with highlighted span:
All of Chopin's compositions include the piano. Most are for solo piano, though he also wrote two piano concertos, a few chamber pieces, and some songs to Polish lyrics.
Sample questions asked by our annotators:
What do all Chopin's songs include?
What musical instrument will we hear in virtually all Chopin's compositions?

Figure 6: Paragraph from SQuAD with two questions for the underlined span

We were mostly interested in spans of text which had more questions in SQuAD already because such spans seemed easier to create questions for. The distribution of questions per span in SQuAD can be seen in Table 2: the vast majority of spans has only one question and having more than four questions per span is very rare. The rightmost column shows how many of such spans were included in our experimental data.

Questions per span	Number of spans in SQuAD 2.0	Occurences in experiment data
1	81619	15
2	2303	15
3	166	15
4	13	10
5	8	5
6	1	0
Total:	84110	60

Table 2: SQuAD 2.0 span distribution

In total, 60 paragraphs were chosen from SQuAD 2.0 randomly but respecting the intended distribution in the third column in Table 2. These paragraphs were machine-translated to Czech and the spans were transferred to Czech manually. Bilingual users then had half of the SQuAD paragraphs in Czech and half in English, monolingual users saw only the Czech paragraphs. No user saw the same paragraph in both English and Czech.

4.2.4. Annotation task composition

The overall composition of types of stimuli is shown in Table 3. The bilingual group received half of the SQuAD stimuli in Czech and half in English. The monolingual group received all the SQuAD stimuli in Czech.
All of the annotators overlap fully in technical and administrative issues. The monolingual annotators overlap fully within the group and 50% with the bilingual group. Such overlaps are necessary for studying the same stimulus answers variations.

Stimuli	monolingual	bilingual
Technical issues	35	35
Administrative issues	30	30
SQuAD 2.0	0	30
SQuAD 2.0 Czech	60	30
Total	125	125

Table 3: Overall composition of the input stimuli

5. Results

Throughout the experiment, we recorded several types of data, while the users interacted with Ptakopět. The list of monitored events is in Table 4 and the description of each recorded information type is in Table 5. Additionally, each logged event contained Unix timestamp.

Event code	Logged data	Description
START	QUEUE	The user logs in
NEXT	SID, REASON	A stimulus is shown
CONFIRM	SID, TXT1, TXT2	User accepts solution
SKIP	REASON	User skips stimulus
TRANSLATE1	TXT1, TXT2	Forward translation is displayed
TRANSLATE2	TXT2, TXT3	Backward translation is displayed
ESTIMATE	ESTIMATION	Quality estimation is highlighted
ALIGN	ALIGNMENT	Source complexity is highlighted

Table 4: Logged information from Ptakopět users for each of their actions

5.1. Basic statistics

We refer to sequences of log entries related to the same stimulus as segments. The number of finished segments, as well as their average duration in every domain, is shown in Table 6. Since the differences in duration between each segment was not high (min 90s, max 106s), we concluded that the users employed similar strategies across all domains and that no domain was exceptionally difficult nor easier than the others.

Logged data	Description
SID	Identifier of the relevant stimulus
TXT1	Content of the source text area
TXT2	Content of the target text area
TXT3	Content of the backward translation text area
ESTIMATION	Quality estimation data
ALIGNMENT	Source to target word alignment
REASON	User's motive for skipping answering the stimulus

Table 5: Description of logged information from Ptakopět users

Domain	Segments	Average duration
SQuAD 2.0	141	100s
SQuAD 2.0 Czech	346	94s
Technical issues	268	107s
Administrative issues	246	90s
All	1001	98s

Table 6: Number of segments and average duration per domain in collected data

5.2. Types of edits

Some of the stimuli were skipped, mostly because the annotators did not have enough confidence in the MT system's performance (for a given stimulus) and were unable to produce a better result. We describe such segments as *skipped* as opposed to *finished*. From the finished ones, about a quarter of the segments were written linearly (no edits or deletions in already written text). Such segments are denoted as *linear* as opposed to segments, which had some edits in already written parts (*with edits*). Number of skipped, finished, linear and edited segments can be seen in Table 7.

We see that the proportion of skipped segments (i.e. segments where the annotator failed to produce an output they could accept) is not excessively high. The easiest to process were administrative issues (5.7 % skipped segments) and the hardest was the technical issues (10.8 %). SQuAD reached 7.8 % (English) and 7.5 % (Czech) of skipped segments.

Of the finished segments, most (72%) were edited and not just linearly written (28%). Additionally in technical issues, the stimulus was the description of the technical problem itself, so the annotators could choose to simply copy this text and paste it in the input window. The number of occurrences of this behaviour is described in the table as *init copy* (60% of all edited). We also measured the number of final inputs, which matched the initial stimulus (*Copy & submit*, 6% of all edited).

We then focused on the segments, which were further edited. We tried to extract the first input the annotator expected to be successful. We call this input *first viable* and choose it heuristically as the longest nonfinal input ending with a punctuation mark. We then compute the similarity between the first viable source/translation and the final

Domain	Description	Segments	Ratio
SQuAD 2.0	Skipped	11 (8%)	(of all)
	Finished	130 (92%)	
	Linear	52 (40%)	(of fin.)
	With edits	78 (60%)	
SQuAD 2.0 Czech	Skipped	26 (8%)	(of all)
	Finished	320 (92%)	
	Linear	110 (34%)	(of fin.)
	With edits	210 (66%)	
Tech issues	Skipped	29 (11%)	(of all)
	Finished	239 (89%)	
	Linear	27 (11%)	(of fin.)
	With edits	212 (89%)	
	Init copy	127 (60%)	(of edt.)
	Copy & submit	13 (6%)	
Administrative issues	Skipped	14 (6%)	(of all)
	Finished	232 (94%)	
	Linear	70 (30%)	(of fin.)
	With edits	162 (70%)	
All	Skipped	80 (8%)	(of all)
	Finished	921 (92%)	
	Linear	259 (28%)	(of fin.)
	With edits	662 (72%)	

Table 7: Number of skipped, finished, linear and edited segments per domain in collected data together with percentage of all, finished or edited segments.

source/translation version as confirmed by the annotator using Gestalt Pattern Matching on word level (implemented in Python's difflib). This similarity is shown per domain in Table 8.

Domain	Source sim.	Translation sim.
SQuAD 2.0	69%	55%
SQuAD 2.0 Czech	75%	60%
Tech issues	78%	67%
Administrative issues	74%	57%
All	75%	61%

Table 8: Similarity between first viable and final versions of inputs (source texts) and outputs (translations) (only on segments with edits)

From Table 8 we can see that even though the first viable and final inputs are quite similar (75% on average across all domains), the first viable and final translations are less similar (61% on average). This indicates that the edits had a considerable effect on the translation.

5.3. Evaluation survey

At the end of the experiment, we asked the annotators to fill in a short survey. The results are shown in Table 9.

We suspect that the overall results are affected by the relatively low quality of the MT system. Most of the annotators complained of this, stating that the MT system made obvious mistakes, such as adding random words. Should we deploy a better MT system, the average scores would probably go up. At the same time, it seems that we have chosen

Question	Domain	Average
What confidence do you have in the translations you have created?	SQuAD 2.0 (both)	1.14
	Technical issues	2.86
	Administrative issues	2.29
	All	2.10
How useful was the highlighting of problematic words in technical issues?		2.29
How useful was the environment for these tasks, compared to other web interfaces (Google Translate, Bing Translator and others)?		1.71

Table 9: Annotator survey results (1 - most, 5 - least)

a good level of MT quality for the experiment: MT was not too good (edits were needed) and not too bad (at most 10.8 % of segments were given up).
The perceived confidence per domain confirms that technical issues were the hardest (probably because of vocabulary deficiency of the MT system in the IT domain) and it was the highest for encyclopedic questions.
Good news is that the overall usefulness of Ptakopět compared to standard web interfaces to MT was rated as 1.71 on the 1–5 scale, although the perceived utility of QE was lower (2.29).
We also inquired about the users' strategies. Most of them focused on the backtranslation to validate the output. If they suspected that the result may not be preferable (either by the backtranslation or by looking at the result itself), they tried reformulating the input by using synonyms. If that did not help, they tried simplifying the sentence, even beyond the threshold of a grammatically sound output sentence, attempting just to communicate the meaning properly.
It is worth noting, that the backward translation can in principle fix previously introduced errors, thus hiding the problem. In these cases, the users could get a false sense of confidence in the translation. For such occasions, an external tool (e.g. MT quality estimator) is needed.

5.4. Output validation

After we collected data from the previous annotation phase, we extracted final translations and translations of first viable inputs for each segment (if possible). We then asked another annotator with a good command of German (C2 on the CEFR scale) to rate each translation on the scale of 1 to 5 (best to worst) estimating to what extent a native German would understand the message.

5.4.1. Validation results

The results for each domain for the final and first viable translations are in Table 10. In each domain, the final translations were much better than the translations for first viable inputs, the average score improves from 3.85 ± 1.44 to 2.77 ± 1.6. Paired t-test showed, that the difference is highly statistically significant ($p < 0.0001$ for 0.75 difference between final and first viable ratings).
The validation scores assigned to the individual segments using a histogram is presented in Figure 7. We see that the first viable translations received mostly the worst rat-

	First viable		Final	
Domain	Avg.	Var.	Avg.	Var.
SQuAD 2.0	3.43	2.56	1.91	2.00
SQuAD 2.0 Czech	3.95	2.18	2.64	2.67
Tech issues	3.77	1.79	3.10	2.23
Admin. issues	4.05	1.91	2.92	2.55
All	3.85	2.07	2.77	2.55

Table 10: Average quality ratings across domains for first viable and final translations (1 - best, 5 - worst)

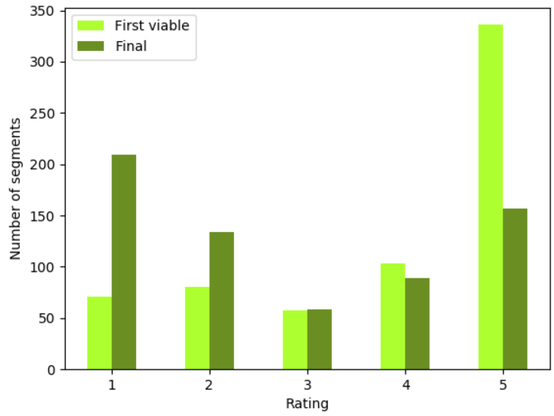

Figure 7: Histogram of ratings for first viable and final translations (1 - best, 5 - worst)

ing while final hypotheses are bimodal: the majority received a favourable validation score but a considerable portion (24%) had the worst score. We assume that in these cases, our setup was unreliable and fooled the user in accepting a misleading translation.
Overall, this is a clear success, as our technique helps people to produce better messages in a language they do not speak. Nevertheless, it is important to mention the limitations of our pilot study. Our heuristics for picking first viable inputs may include sentences, which were actually not thought to be viable by the user. Maybe the sentences contained obvious errors, such as typos, which the user would fix anyway but maybe the user would not notice if we did not present the backtraslation. A more thorough exploration is needed to isolate such effects.

5.4.2. Validation by sentence length

One could expect that shorter sentences are generally easier to process by MT (except for very ambiguous very short sentences). To analyze this assumption in our setting, we plot the average validation score assigned to sentences based on the source length.
Figure 8 indicates, that the assumed effect is not apparent in our case, at least not with our estimation of first viable hypotheses. The shorter sentences generally receive worse validation scores than longer ones, but the differences are not very big.
For final hypotheses, the assumption seems more true: The best validation score was assigned to sentences of 6–10

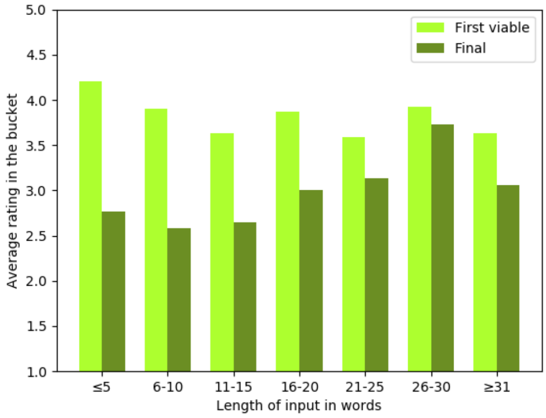

Figure 8: Average rating for first viable and final translations based on the translated sentence length (1 - best, 5 - worst)

words and the worst to sentences over 25 words. A noteworthy observation is that for these long sentence, the improvement in the validation scores from first viable to the final hypothesis is very low.

6. Conclusion

In this paper, we presented Ptakopět, a modular system for outbound translation. Ptakopět allows users to produce messages in a language they do not speak and still gain some level of confidence in the resulting translation.

In a pilot experiment, users who did not know German were tasked to use this system for real-world use cases (communication with IT support, describing administrative issues and asking encyclopedic questions).

Across these domains, 5–10 % of inputs could not have been translated (our annotators have given up). For the submitted translations, the average self-reported confidence in the translations was 2.1 on a 1–5 (best–worst) scale and the tool was found more useful than standard web interfaces to MT (average usefulness of 1.71, same scale).

The majority of inputs were edited and while initial inputs and the final inputs were quite similar in the source language (word-level Gestalt Pattern Matching similarity of 75 %), the translations of them differed more (average similarity of 61 %).

The second, validation, phase of our experiment confirmed that overall understandability of the translations improved from 3.9 to 2.71 on the 1–5 (best–worst) scale.

In future, we plan to refine the experiment design and consider also other features of the outbound translation user interface. For instance, we could directly estimate the chances of translating a word correctly by considering the number of occurrences in the training corpus of the underlying MT systems, or we could offer synonyms to poorly covered source words (based on a large monolingual corpus). The evaluation could also contrast how much each of these features helps in the task of producing a message in an unknown language.

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Bibliographical References

Dyer, C., Chahuneau, V., and Smith, N. A. (2013). A simple, fast, and effective reparameterization of ibm model 2. In *Proceedings of NAACL-HLT*, pages 644–648.

Ive, J., Blain, F., and Specia, L. (2018). Deepquest: a framework for neural-based quality estimation. *In the Proceedings of COLING 2018, the 27th International Conference on Computational Linguistics, Sante Fe, New Mexico, USA*.

Kepler, F., Trénous, J., Treviso, M., Vera, M., and Martins, A. F. T. (2019). OpenKiwi: An open source framework for quality estimation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics–System Demonstrations*, pages 117–122, Florence, Italy, July. Association for Computational Linguistics.

Kim, H., Jung, H.-Y., Kwon, H., Lee, J.-H., and Na, S.-H. (2017). Predictor-estimator: Neural quality estimation based on target word prediction for machine translation. *ACM Trans. Asian Low-Resour. Lang. Inf. Process.*, 17(1):3:1–3:22, September.

Kreutzer, J., Schamoni, S., and Riezler, S. (2015). Quality estimation from scratch (quetch): Deep learning for word-level translation quality estimation. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 316–322.

Kvapilíková, I., Macháček, D., and Bojar, O. (2019). CUNI systems for the unsupervised news translation task in WMT 2019. In *Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1)*, pages 241–248, Florence, Italy, August. Association for Computational Linguistics.

Martins, A. F. T., Astudillo, R., Hokamp, C., and Kepler, F. (2016). Unbabel's participation in the WMT16 word-level translation quality estimation shared task. In *Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers*, pages 806–811, Berlin, Germany, August. Association for Computational Linguistics.

Martins, A. F., Junczys-Dowmunt, M., Kepler, F. N., Astudillo, R., Hokamp, C., and Grundkiewicz, R. (2017). Pushing the limits of translation quality estimation. *Transactions of the Association for Computational Linguistics*, 5:205–218, May.

Popel, M. (2018). CUNI transformer neural MT system for WMT18. In *Proceedings of the Third Conference on Machine Translation: Shared Task Papers*, pages 482–487, Belgium, Brussels, October. Association for Computational Linguistics.

Rajpurkar, P., Jia, R., and Liang, P. (2018). Know what you don't know: Unanswerable questions for squad. *CoRR*, abs/1806.03822.

Somers, H. (2005). Round-trip translation: What is it good for? In *Proceedings of the Australasian Language Technology Workshop 2005*, pages 127–133.

Specia, L. and Logacheva, V. (2017). WMT17 quality estimation shared task training and development data. LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics (ÚFAL), Faculty of Mathematics and Physics, Charles University.

Specia, L., Paetzold, G., and Scarton, C. (2015). Multi-level translation quality prediction with quest++. In *ACL-IJCNLP 2015 System Demonstrations*, pages 115–120, Beijing, China.

Tiedemann, J. (2012). Parallel data, tools and interfaces in opus. In Nicoletta Calzolari (Conference Chair), et al., editors, *Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC'12)*, Istanbul, Turkey, may. European Language Resources Association (ELRA).

Varga, D., Kornai, A., Nagy, V., Németh, L., and Trón, V. (2007). Parallel corpora for medium density languages.