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DEPARTMENT OF FOREIGN LANGUAGES
ÚSTAV JAZYKŮ

EFFECTIVENESS OF MACHINE TRANSLATION
EFEKTIVNOST STROJOVÉHO PŘEKLADU

BACHELOR'S THESIS
BAKALÁŘSKÁ PRÁCE

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Bakalářská práce

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NÁZEV TÉMATU:

Efektivnost strojového překladu

POKYNY PRO VYPRACOVÁNÍ:

Cílem práce je zhodnotit možnosti a efektivnost strojového překladu v dnešní době, stejně jako pojmenovat faktory, které efektivnost a "věrnost" překladu ovlivňují. V prakticky hodnotící části by měla být hlavní pozornost věnována překladačům založeným na tzv. "neurálních sítích".

DOPORUČENÁ LITERATURA:

Ekbia, H. R. (2008). Artificial dreams: The quest for non-biological intelligence. Cambridge UP.

Rojas, R. (2013). Neural networks: a systematic introduction. Springer.

Machine Translation (časopis, 2000-2016)

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Vedoucí práce: Mgr. Miroslav Kotásek, Ph.D.
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Abstrakt

Práce hodnotí strojový překlad z hlediska problémů kterým čelí, popisuje nejčastější metody a přístupy a s pomocí praktických ukázek překladů, hodnotí, kvality a možností využití. Problémem jsou v první řadě odlišnosti mezi jazyky, které mohou mít odlišnou flexi, mluvnické kategorie nebo slovosled, a jsou tedy vyžadovány metody, které by tyto morfologické, gramatické a syntaktické odlišnosti zohledňovali. Další problémy jsou na úrovni sémantiky, kde musí překladače správně identifikovat význam slova a zvolit vhodný překlad. Ovšem možnosti porozumění významu jakožto i zohledňování kontextu jsou u počítačů omezené, stejně tak jako větší překladatelská rozhodnutí ohledně celého textu. Úspěšné řešení těchto problémů by vyžadovalo kompletní umělou inteligenci, která však v současnosti není k dispozici. Nejvyšší úrovně umělé inteligence dosahují patrně překladače, používající neuronové sítě, což je nejmodernější metoda strojového překladu, kterou již používají i některé běžně dostupné internetové překladače. Praktická ukázka na několika typech textů, přeložených z angličtiny do češtiny a naopak pomocí Google Translate ukázala, že strojový překlad pomocí neuronových sítí se velice úspěšně vypořádává s množstvím jazykových odlišností a dovede překládat termíny a delší fráze, stále ovšem produkuje množství chyb často bez předvídatelné příčiny a jeho chování je celkově nekonzistentí a citlivé na změny. Doposud tedy neexistuje universální systém, který by byl schopen plně automatického překladu vysoké kvality. Aplikace strojového překladu je vždy omezena buď sníženou kvalitou textu, nebo nutností návrhu systému pouze pro specifický účel a omezené pole působnosti. Strojový překlad tedy může zvyšovat efektivitu překladu jako takového pří nutnosti lidského zapojení, ale v dohledné době nenahradí lidské překladatele.

Klíčová slova

neuronový strojový překlad, pravidlový strojový překlad, statistický strojový překlad, umělá inteligence, neuronové sítě, hodnocení překladu

Abstract

The thesis considers machine translation(MT) in terms of difficulties it deals with, describes the most common methods and, with practical examples of MT, evaluates its quality and possible applications. In the first place, the MT has to deal with differences between languages, which can have different inflection, grammatical categories and syntax. Methods to deal with morphological, grammatical and syntactical differences are therefore required. Another problem is on the level of semantics; the MT systems must successfully identify meaning of words and choose appropriate translation. However, the computers have only limited capability in understanding of the meaning and considering context, as well as in making greater decisions about the whole text. To successfully deal with all problems of translation, a complete artificial intelligence would be required, which is not yet available. The most advanced in terms of AI seems to be the neural machine translation, which is the most modern method already used by online translators. The practical example of translation of several types of texts from English to Czech (and from CS to EN) with Google Translate shows that NMT can cope with many language differences and it can often successfully translate terminology and longer phrases, but it still produces a large number of mistakes, reason for which cannot be observed directly, and its behavior is inconsistent and sensitive to any change. To this day, there is still no universal system that would be able to produce Fully Automatic High-Quality Translation. MT application is restricted either by reduced quality of the output or by designing MT system only for specific field or purpose. MT can overall improve translation efficiency, while human involvement is required, but it will not replace human translators in the near future.

Keywords

neural machine translation, classical machine translation, statistical machine translation, artificial intelligence, neural networks, translation evaluation

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Poděkování

Rád bych poděkoval vedoucímu svojí bakalářské práce Mgr. Miroslavu Kotáskovi, Ph.D. za vedení při psaní práce, konzultace, průběžné kontroly a množství podnětů k vylepšení a dokončení mojí práce.

Prohlášení

Prohlašuji, že svůj semestrální projekt na téma Efektivnost strojového překladu jsem vypracoval samostatně pod vedením vedoucího semestrálního projektu a s použitím odborné literatury a dalších informačních zdrojů, které jsou všechny citovány v práci a uvedeny v seznamu literatury na konci práce.

Jako autor uvedeného semestrálního projektu dále prohlašuji, že v souvislosti s vytvořením tohoto semestrálního projektu jsem neporušil autorská práva třetích osob, zejména jsem nezasáhl nedovoleným způsobem do cizích autorských práv osobnostních a/nebo majetkových a jsem si plně vědom následků porušení ustanovení § 11 a následujících zákona č. 121/2000 Sb., o právu autorském, o právech souvisejících s právem autorským a o změně některých zákonů (autorský zákon), ve znění pozdějších předpisů, včetně možných trestněprávních důsledků vyplývajících z ustanovení části druhé, hlavy VI. díl 4 Trestního zákoníku č. 40/2009 Sb.

V Brně dne . ...

(podpis autora)

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List of Used Abbreviations

CMT	Classical Machine Translation
CS	Czech
EN	English
FAHQT	Fully Automatic High-Quality Translation
HAMT	Human-Aided Machine Translation
MAHT	Machine-Aided Human Translation
NMT	Neural Machine Translation
SL	Source Language
SMT	Statistical Machine Translation
TL	Target Language

1 Introduction

The human evolution and history naturally resulted in the existence of many languages all over the world, creating vast cultural diversity and a resourceful environment for many researches and scientists – linguists, anthropologists, philosopher to mention only a select few. Not only is it a challenging field of study, it is also inspiring to see how other cultures perceive and structure their reality through language. On the other hand, this diversity is rather undesirable in some areas, especially when the cultural differences are of lesser importance. In engineering, medicine, and sciences in general, but also in business, law, and bureaucracy, it is more efficient to use only one language for the all participating parties to communicate successfully, or translation has to be included in the process.

Along tendencies and efforts to use only one language in various fields of international and cross-cultural cooperation (where English serves as lingua franca most often), there is also growing demand for translations to enable efficient communication. The demand exists also among common internet users; the internet allows information to be accessed from all over the world. Here, translation again plays important role since it enables the information to be not only accessible, but understandable as well.

It would be beneficial to economize and possibly even automatize translations by delegating this task to computers. Indeed, efforts to create automated translation engines are one of earliest non-computational applications of computers, while the first working systems date back to 1950's. To this day, after more than 65 years of development, there is no system that would be able to produce Fully Automatic High-Quality Translation applicable in any field to any type of text, but the field has not been abandoned, and the machine translation is widely used and developed especially today with improving performance and accessibility of online translators.

Though the aim and the ideal output that both human and machine translators try to achieve is the same, the process of machine translation is very different from work of a human. The properties and features of different languages and translation procedures, which the humans learn to handle intuitively during language acquisition and the practice of translating, must be addressed directly in MT. The designing therefore requires a certain linguistic knowledge in combination with programming skills; it must deeply

investigate the process of translation and define its individual aspects and then create computer algorithms and methods to replicate them.

The purpose of this thesis is to identify problems that the MT encounters, describe its methods and ways of evaluation, and in the end, consider its quality, and find the possible applications and uses that the machine translation has in present days. The first part of this paper describes various language and translation problems relevant for the machine translation and consequent AI requirements that would be required for a machine translation to match the human translators in its quality. Next, methods of the classical machine translation, widely used statistical machine translation, and the new, prospective neural machine translation are described. The last part is devoted to the actual state of the technology accompanied by practical examples of translation of a language pair Czech and English with the possibilities of application.

The term *machine translation* (MT) is here understood in a basic, almost intuitive form, as a computer method for converting/translating of a written text encoded in a format recognizable by computers from a source language (SL) to a target language (TL). There are other modifications of MT such as processing and translating of a speech input, or recognition and translation of a hand-written text from a graphical input, a convenient method of translating of languages that use symbol system other than Latin. However, these more advanced approaches are not discussed in this thesis as the basis of any high-quality MT is always profound text-to-text translation.

2 Language Differences

During early development of machine translation, the first method was to directly substitute a word in a source language with a word in a target language and this approach was called direct translation. Obviously, such method could hardly be successful on its own, since languages differ on various levels – morphologic, syntactic, semantic, etc., and in machine translation, these differences have to be addressed and dealt with. Simple word-for-word substitution is not possible in MT for multiple reasons. The purpose the following chapter is to identify some of the most relevant differences, that have to be considered and that make the MT an uneasy task.

2.1 Morphology

When dealing with machine translation, the first problem that we encounter are the morphological differences. Languages are commonly differentiated as analytical, agglutinative and synthetic. English (EN) is an example of analytical language, which means that there is a frequent one-to-one relation of words and morphemes (Moravcsik, 2012). On the other hand, Czech(CS), which will serve as a reference language for comparison and translation, displays a higher ratio of polymorphemic words and is therefore considered a highly synthetic language (Dušková, 2012). The presence and role of morphemes vary in languages and very often, a single word of one language can be represented by multiple ones in another.

The most significant appears to be the problem of inflection, which is used to express different grammatical categories – e.g. for only two forms of an English substantive (singular and plural), we have to consider multiple forms for seven cases in Czech, while sometimes, there can be multiple possible forms for a single case. In agglutinative languages, various forms of affixes have to be considered. The classical MT systems then require lexicons defining all possible variations and mechanisms for choosing the right form (Hutchins & Somers, 1992), MT systems based on statistical analysis use different approach, where it analyzes position of the word in a phrase.

On the other hand, the situations in which affixes are used to form a new word belonging to same or different word class, which is common in English (e.g. *common > uncommon; commonly*) should not be a problem, because in lexicons it is usual to list every individual word (in its basic form, if the inflection is present).

2.2 Syntax

Another obvious feature, in which languages differ is word order. Having limited possibilities of inflection, English strongly relies on word order to determine the syntactic function of words in sentences. In Czech, on the other hand, the word order only plays secondary role in determining syntactic relations (Dušková, 2012). At this point, the direction of translation influences the quality and the required mechanism – while sentence directly translated form EN to CS might be correct in terms of word order, translation from CS to EN might produce a wrong output.

Czech also does not require a subject to be present in a sentence, so a simple reordering of words to fit the word order of target language is not sufficient. A mechanism is then required to determine and add the right form of missing subject. On the other hand, English uses the articles, which have no straight counterpart in Czech. For translation form CS to EN, the articles would have to be added (and the use of right article determined); for translation from EN to CS, a simple solution would be to omit the articles, but since they have the role of determiners in the language, it would decrease the quality of the translation.

2.3 Semantics

While grammatical and syntactical differences between languages theoretically allow to define explicit and specific rules to deal with them, the semantic aspects of languages require computers to be able to derive meaning of words and phrases in order to choose appropriate translation. In the first place, instances of polysemy and homonymy require to be distinguished properly in the SL (e.g. noun has to be distinguished from a verb with the same form). Secondly, the right translation needs to be chosen in the TL if word diverges into multiple possible translations. Some of these problems can be resolved by analyzing the syntactical position of a word; in other cases, analysis of collocation might be sufficient, but some might require consideration of context in order to choose the right term.

Apart from being able to identify the correct meaning of a word in one language, the MT engine also must be able to choose a proper translation in case of homonymy or polysemy. Though this task can be simple for some most common terms, it is complicated to ensure adequate choice on the full scale. The problem arises when we consider the properties of signs and how they represent reality. A sign can be understood as a relation between a spoken or textual form of a word (*signifier*) and the mental representation of reality it stands for (*signified)*. Usually, a sign indirectly relates to some object or aspect in the reality, but in communication, we only use its concepts in our minds, not the objects themselves (Chandler, 2007). In the ideal case, the reality we refer to and thus our concepts about it would be the same for all people regardless of the language. A very simple scheme of translation could then be derived (*Figure 1*). Consequently, the easy task of a translator would be to know the proper associations in both source language and

Figure 1 Translation according to Signifier-Signified pair

in target language and to perform adequate transformations for the translation to be successful.

The nature of language is, nonetheless, more complicated. As was already mentioned, the signified is only a mental representation rather than reality itself, and hence, it is considerably subjective. Of course, certain parity exists among individual users of one language, otherwise communication would be impossible; still, everyone can have a slightly different schema for each sign in his mind. When a term is translated into another language, the difference can increase and it becomes harder to ensure sufficient closeness of concepts expressed by two different words in different languages.

The issue becomes more complicated, when we consider that it is the language that constrains the way reality is structured. In brief, Sapir-Whorf hypothesis claims that the structure of language affects its speaker's cognition of the world and not the opposite (Werner, 1997) . Put into an extreme, we can regard the reality as a continuous vague mass, parts of which do not become distinguished until we analyze it and split it into pieces, to which we give names. This process is individual for each language (or group of languages), and therefore, every language structures reality differently. On the other hand, there are probably some common categories in the world that are distinguished similarly in various languages. Anyway, purpose of my thesis is not to determine, to what extent language affects the perception of the world and how much the opposite holds; here, it is enough to take the linguistic relativity principle into account. It causes languages to be somewhat (sometimes significantly) different in categories, attributes and associations they distinguish.

An example of ancient Chinese, though being a rather exotic, can demonstrate this difference very well. Word "*tao*" can be translate as "meaning", "path" or also "pole" while these should not be perceived as multiple unrelated meanings of the world, but only one, which doesn't have any equivalent in English, nor Czech (and probably any western language). In book I Ching, the symbol "*chen*" stands for *thunder*, *wood* and *the one that excites/initiates*, and its opposite is "*sun*" which means *wind*, *gentleness* and also *realization*/*execution*. Another pair of opposites is "*tuej*" - *lake*, *steam*, *happiness*, and "*ken*" - *mountain, calmness, meditation* (Jung & Wilhelm, 2004). Such associations of rather metaphorical character are based on very specific culture-dependent perception of reality and they are impossible to be found in western languages. Therefore, we are unable to represent them by a similar word that would successfully maintain all its meanings and connotations.

These basic ideas from philosophy of language show that difference in languages is not merely in usage of different symbols for the same concepts. This disparity might not be so considerably large when describing the natural world, where common categories and objects can be identified more easily. The problem becomes more complex when languages refer to abstract terms describing for example human characteristics, or culture-specific products and categories, religion and moral terms. Human translators can overcome some of those problems by using proper analogies, comparisons or metaphors. They are free to try to deliver the meaning by deeper explanation, explification or different formulation. On the other hand, the basic unit that a classical MT computers usually translate is a single word, which is not sufficient in most cases.

To this point, only meaning of a single word was considered. However, often a lexical item is not represented by one word but by a phrase. The deeper level of analysis of a SL text should therefore distinguish between words that can be translated separately and between phrases that needs to be translated as a whole. A lexicon then would require not only simple word-to-word entries, but also phrases-to-word translations, would greatly increase its size and also time required for its production.

3 Translation Methodology

3.1 Achieving equivalence

To define what translation is or even to specify what a translation should look like is a task that is hard to accomplish. A very basic definition based on intuition could be phrased as follows: "transformation of word, text, speech, etc. from one language to another". Such trivial answer could probably be obtained from any person non-educated in relevant fields, and would be fully sufficient for general public. Indeed, the task of translator can appear very simple – take a product of one language and make it understandable for users of another language. However, anyone who has at least little experience with translation would agree that this goal is not easy to achieve. The basic definition of the verb "translate" given by Oxford dictionary (Oxford: Ilustrovaný anglický výkladový slovník (*Oxford: Ilustrovaný anglický výkladový slovník*, 2011)) is already more profound: "express the sense (of word, speech, etc.) in another language." The only obvious difference from the definition given previously lays in the word "sense," which, however, plays a major role as the aim of translation is to deliver this sense. However, the word itself is rather vague and does not provide a clear idea of what the translation should look like or how the sense should be delivered.

The language disparity – especially on the semantic level, described in the previous section, leads to the problem of equivalence, which is a pivotal issue of translation. Various authors propose different theories of equivalence and how it should be obtained. It can be sought on different levels and opinions on which is the most important differ. One of the equivalences that is often emphasized is the functional equivalence as proposed by the functional approach to translation. According to this theory translation should fulfill the same function in TL as the original text does in SL. It should contain not only the referential/denotative aspect, but also connotative and pragmatic (Knittlová, Grygová & Zehnalová, 2010).

The usual approach to achieve equivalence, recommended in translation guides, is to start with the bigger picture and see the whole text in context and then move to more detailed decisions bearing the context in mind (Knittlová, Grygová & Zehnalová, 2010). The first task that is advised to any translator is to read thoroughly the translated text, assess the author's intentions, style and approach to readership, identify problematic passages and terms and make general decisions before moving to specific problems

(Newmark, 1988). Newmark further believes that translation is never completely objective nor subjective, it is always “more or less” and that there are no absolutes such as “always” and “never” (ibid). Such conclusion is troublesome for MT, because computers can only work with definite inputs and outputs – zeros and ones.

Indeed, the process of translation is rather intuitive and often hard to analyze to a greatest detail. A deep investigation of it would be required to allow to design formal rules that could be replicated by computers. From the history of development of MT system, it does not seem that they tried to find inspiration in the performance of human translators. Instead, the MT started from a scratch with the simplest transfer operations and gradually developed more profound rules and methods to improve its quality. As will be seen in the chapter *5 Machine Translation Methods*, the most successful contemporary MT engines use processes that seem to be quite different from approaches of human translators.

In general, the translator’s skills that ensure a high quality of translation do not include only language competence, but also cultural knowledge and knowledge of the field of translation and analytical thinking. The process of translation then includes broader decisions about how to approach the text, how to translate certain repeating terms and expressions and how to maintain consistency. At this point, it is hard to implement such functionality into MT; needless to say, a system that would perform the same operations as a human translator would be extremely complicated to design and maintain.

3.2 Restricted scope and purpose of MT

However, translation might not be regarded as a universal process, where the same strategies and methods apply to any type of text. The circumstances of text creation and its purpose are often very different and consequently the requirements for proper translation and also the problems that can be encountered vary. In analogy to individual human translators, who have different skills and experience and are therefore assigned the translations in which they perform best, it might be beneficial to consider the properties of a text in advance and see whether or not the MT might be a suitable approach.

A difference should therefore be made between literary and non-literary (or technical) texts and their translations. Literary translation has different purposes and priorities than the non-literary; it aims mainly for aesthetic goals and it tries to entertain

the reader, involve him or her in the story, arise interest, and style of an author plays major role. These goals can be achieved in various ways during translation, involving many global and local decisions, of which the MT is not capable. Though MT of literary works is considered in research, it is not on a large scale, and is generally considered of no importance for MT or even as something that MT should not attempt. The improvements in the MT methods should be especially in addressing "greater-than-sentence-level" features of texts in order to allow the literary MT translation (Voight & Jurafsky, 2012). Even so, such translation would still probably be only informative, narrating story in understandable but not very interesting manner. The purpose of non-literary texts, on the other hand is mainly to deliver information, while other aspects such as aesthetics and even naturalness are of lesser importance, and this is where the use of an MT can be most fruitful or even beneficial (Trujillo, 2012).

An alternative theory of translation called *skopos theory* might then provide justification for the abilities of MT. It states that what drives the action of translating is its purpose, the intention with which it is created. It sees the source text as an offer of information, which can be provided to speakers of another language in the form of a target text. This theory can be best applied to non-literary texts, where conveying of information is the most important aspect (Du, 2012). For example, if a reason for translation of a cooking recipe is to prepare certain food, then the translation is successful when the reader can do so.

The skopos theory therefore involves the economic factors of the translation, where the high speed or low cost of translation can be a reason to settle for a lower quality. The most obvious advantage of MT is its high speed and automated operation, and its use might reduce the time that a human translator has to spend with the translation. Such features are attractive especially in business, for example, when producing technical documentation and providing same information for readers in multiple languages.

4 AI requirements

Considering all the problems that can arise, translation can seldom be fully successful and complete even when performed by humans. As the complexity of message rises and more sociocultural factors are involved, the more difficult it is to preserve the full meaning of SL message, including its connotations, cultural associations, symbolism

and the desired purpose and impact on the reader. This task is complicated for human translators; it requires skill and experience as well as intuition. However developed and elaborate abilities of computers can be, they cannot achieve such level of proficiency. On one hand, computer can read a text much faster than a human and analyze it in terms of lexis, and based on statistical methods it can probably determine the genre and register used, for example. But how can it decide an author's intention, and make decisions about other attributes of the text that require understanding?

All that computers can do is make links and associations (they can be given to them or computers can learn them), but they are unable to understand the meaning on this basis- In a bilingual dictionary database, a link can be made between "*train*" and "*vlak*". When this link changes to "*jahody*," for example, the computer has no way to discover. Some correction methods can exist based on statistical probability, but never on inherent meaning of used symbols.

Chinese room argument, introduced by John Searle in 1980, is a well-known argument that claims that computers cannot understand the meaning of symbols. In his thought experiment, he describes a situation, in which a man with no knowledge of Chinese is in a room with Chinese symbols on cards (a database) and a book or a manual on how to manipulate these symbols (syntactic rules). He is then slipped papers with questions written in Chinese (an input) underneath a door, and based on the rules available he creates answers from the database (an output) and passes it back. To a person asking questions, it would seem that the operator in the room understand Chinese, which is obviously not true, because the operator only knows the formal rules of how to manipulate the symbols (Cole, 2015).

A similar situation can arise in machine translation, when computer translates messages from one language to another. It appears to understand both languages and the translated message while processing an input and creating a corresponding output, but in fact it only performs transformations based on formal rules or links. The computer has no idea what the text is about. Therefore, it leads to the suggestion that computers have major limitations on the semantic level already. If they do not know what the word means, they cannot choose the right equivalent in case of homonyms, for instance.

If computers fail at the semantic level, they can barely succeed, when pragmatics aspects are considered, i.e. to properly understand the cohesive chains, the information

"between the lines," the situation of utterance, etc. Going even further, the computer's task becomes near to impossible when it is asked for example to assess the author's intention – it would assume that computer can understand human motivations and aims, that it has some empathy or even hermeneutical skills. Such demands are often too much to ask of people let alone computers. From this perspective, the problem of MT starts to relate to the topic of artificial intelligence. The speech processing and AI are closely interconnected – it is generally thought that to learn computer to think requires making it understand language.

Reviewing the criticism that followed Searle's Chinese room argument, it seems that there is no clear consensus about how mind, understanding or intelligence can be defined and identified (Cole, 2015). One bone of contention seems to be in the disagreement, whether the proper manipulation with symbols is enough to prove that the machine "understands." The operation of human brain is not fully explained and we might therefore be, in an extreme case, only machines with immense computational power, which process inputs and generate outputs based on some highly complex internal rules, and the resulting behavior would be, what is called the mind. It is therefore hard to consider, at which conditions would the MT system be able to really understand meaning.

The original Chinese Room Argument aims against so-called "strong AI," which represents the claim that suitably programmed programs can have the ability to understand natural languages and have other mental human-like capabilities (Cole, 2015). Should the MT systems ever be able to make same decisions as human translators and produce *Fully Automatic High-Quality Translation* (FAHQT), they probably need to fulfill the strong AI claims. These requirements could probably be achieved only by a complete AI, a system with abilities to learn and understand on the same level as humans. Complete AI should be able to cover a wide range of tasks related to natural language processing (e.g. having conversation, look up and answer questions, assist with research) and it could consequently be assigned with translation as well. A consequent MT system might come closer to the methods of human translators, make similar decisions and fulfill the aforementioned demands. Needless to say, such expectations from computers are still only a science fiction and advances towards their design are issue for the field of AI in general and not of the field of MT itself.

From an alternative, and probably more realistic, point of view, an artificial system can be deemed “intelligent” because of its ability to perform a certain specific task such as the MT. The system is then evaluated for what it does; not what it should do in the most ideal case. An MT system could then be able to produce an output, comparable to human translations in its quality, while it might not perform the same steps as human translator. This approach is more suitable for the MT since, as was already mentioned, the process of translation is not fully analyzed and formalized into well-defined separate procedures. However, considering the multiple translation-related problems and demands, it is then uncertain, whether such AI system is ever able to approach the FAHQT and reach the same quality as humans.

5 Machine Translation Methods

The history of machine translation dates back to 1950’s, when computers were becoming to be utilized on a greater scale. The idea of MT was widely introduced in 1949, the first MT conference was held in 1951 and the first public demonstration of MT system by IBM was performed in 1954 (Hutchins & Somers, 1992). At first, there was a large anticipation towards the possibilities of MT, and in the following 20 years, many investments were made into the effort to create a fully automatic MT especially in the United States. As Hutchins further writes: “Optimism had been high, there were many predictions of imminent breakthroughs but disillusionment grew as the complexity of the linguistic problems became more and more apparent.” This disillusion led to another extreme position stating that “there is no immediate or predictable prospect of useful Machine Translation” (Hutchins & Somers, 1992), and to a significant decrease in MT research funding in the US. For the next two decades, MT development continued mainly in Europe and Japan. Later the interest in MT increased again, in late 1990’s there were already capable MT engines on personal computers and statistical MT was developing with increasing computational power. This era was marked with the introduction of phrase-based statistical machine translation which is still being developed to this day (Trujillo, 2012). In the last few years, there is also a great development of the neural machine translations (Cho, van Merriënboer, Bahadanau & Benigo, 2014), which originate in statistical MT, but gradually individualized as a standalone approach and, for its success, it becomes widely used (Britz, Goldie, Luong & Le, 2017).

Three basic types of machine translation will therefore be dealt with here – *classical machine translation (CMT), statistical machine translation (SMT)* and *neural machine translation (NMT).* The first employ analysis and transformation rules on semantic and syntactic level, translating words and expressions and changing word order. The latter two, try to find the most probable translation for pieces of text based on large bilingual corpora, but both with significantly distinct computational methods.

5.1 Classical Machine Translation

The classical MT, sometimes also referred to as rule-based MT, represents the oldest approach and it is the result of over 65 years of development. It is probably the most straightforward method that one would choose when designing a computer program for translation as it directly addresses various inter-language differences discussed in chapter *2 Language Differences*. The CMT is based on large lexicons with word-to-word correspondences and with transfer rules about how to change form of the words and word order. It can be performed on multiple levels from a direct approach to a very abstract one. Possible levels of classical MT can be comprehensively viewed in the *Vauquois triangle* (*Figure 2*). Each vertical step upwards in the Vauquois triangle means more complex analysis and generation, while the horizontal direction represents amount of effort needed for the transfer. Therefore, in the interlingua technique the transfer is minimal, but it requires profound analysis and generation; the opposite holds for direct translation (Trujillo, 2012). The depth of analysis and generation also corresponds to the development of classical MT, where the direct translation is the oldest method (Hutchins & Somers, 1992). There is no clean division between the methods, it is merely an increasing level of abstraction. Various methods can be combined to produce optimal result.

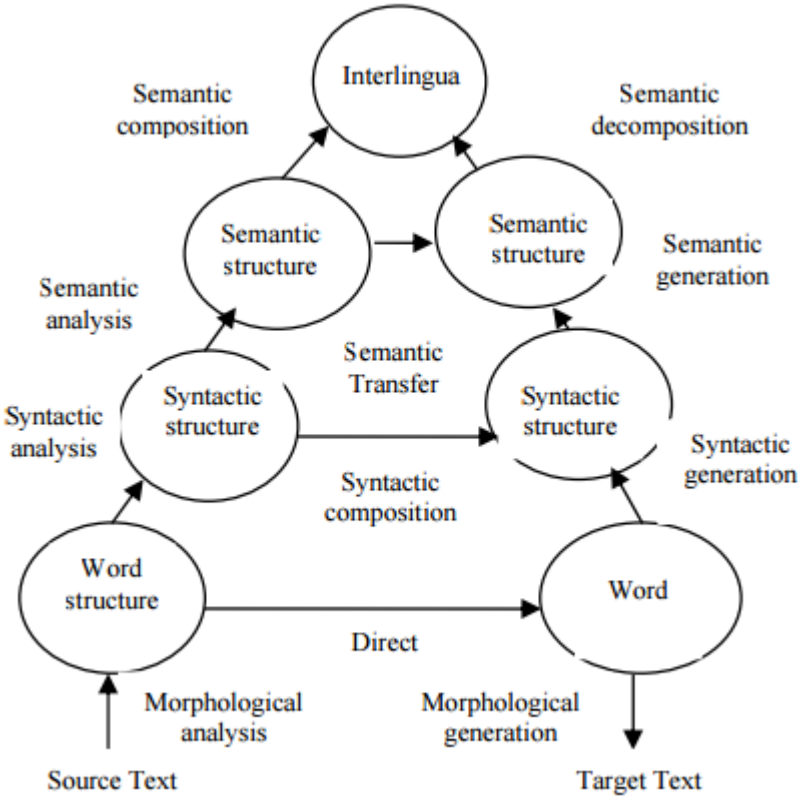

Figure 2 The Vauquois Triangle (Unnikrishnan, Antony & Soman, 2010)

In direct translation, which was the oldest approach used by first MT systems, single words of the SL are first individually translated and then their order is changed to fit the TL. The direct method is not used individually anymore - usually at least shallow lexical analysis is included (Jurafsky & Martin, 2009). Syntactic analysis includes parsing and determining structure of a sentence, individual phrases and their dependencies. Semantic analysis tries to further identify functions of phrases and words, for example properties of a noun in a noun phrase (color, size, etc.), or adverbials (time, location). The text is, therefore, first parsed into individual phrases according to their dependencies and formalized into grammatical or semantic categories (Trujillo, 2012). Then the phrases are reordered and modified, and as a last step, translated. The transfer allows more profound understanding of the text, better word reordering and choice of right word form in case of flection for example.

In the *interlingua* approach the level of abstraction is the highest. Interlingua is a language-independent representation of reality. Translation first tries to extract the meaning(sense) of a SL text (or rather only of a sentence) and create a language-free

representation of the text, and then tries to reconstruct the same meaning in TL (Jurafsky & Martin, 2009). The so-called language-independent representation is, in fact, created with a computer language, so it is only a shift from a natural language to a computer language. A subject, a verb, an object and other possible parts of sentences are individually derived and their properties are marked, so the interlingua representation for a sentence "*John did not buy a new CD.*", can be following: [EVENT: BUYING; AGENT: JOHN; TENSE: PAST; POLARITY: NEGATIVE; …] (adaptation of demonstration in Jurafsky & Martin, 2009). With this information, a sentence can be translated into any language for which there are necessary rules.

The main advantage of interlingua approach is its ability to work with many languages at the same time and the fact that it does not require translation rules for individual pairs of languages. (Jurafsky & Martin, 2009). An essential drawback appears to be that this approach requires that there is one-to-one correspondence of categories and types of clauses, and it assumes that in general, exactly the same piece of reality can be expressed equally in many languages. This approach would be best fitting for the ideal case represented in *Figure 1*. The interlingua method is limited to what can be expressed in the used computer languages, basis for which is most often English. It must, therefore, lead to under-translation, and it cannot be used as a full and universal MT system.

The CMT system can be either bilingual or multilingual, unidirectional or bidirectional. Its advantage is that it theoretically allows us to create rules for almost all possible differences between two languages. However, it appears to be only an ideal case – in fact it is hardly ever possible to cover all the rules and to avoid ambiguity. Furthermore, creation of classical MT software is rather time consuming. The MT systems are often unidirectional and even the bidirectional systems require individual set of rules for any SL – TL combination, so there has to be one set for English-to-Czech and another set for Czech-to-English. A hub language can be used into and form which translation is done, which somehow limits the number of required rule sets (Trujillo, 2012). A modularity on the other hand is an advantageous property of such MT systems; it allows specific mechanisms and algorithms to be added and removed as required and more universal rules can be used in multiple language combinations without a need to create the rules again (Hutchins & Somers, 1992).

To this day, there have not been a fully successful classical MT engine. Therefore, it seems that the direct addressing of language differences and translation problems is not possible on the full scale as the complexity and variability of languages is too large. This field is still being developed and taught, but its application is more suitable for specific tasks. Other MT approaches are developed more often in the effort towards FAHQT (Bojar et al., 2016)

5.2 Statistical Machine Translation

Having a large number of human translation, we can see that not only individual words, but also phrases are likely to be translated similarly. Translations follow certain patterns, which can be observed and re-used in other translations. The SMT therefore does not require vast linguistic knowledge and uses instead distributional properties of words and phrases to find the most likely translation (Trujillo, 2012).

No transfer rules or bilingual dictionary is required, instead monolingual and bilingual corpora are processed and used for learning the probability of a SL expression being translated as a certain TL expression. During analysis, the monolingual corpus is used to determine, which word sequences in TL are correct. In the bilingual corpus, sentences are first matched according to their length and position, and then the word and phrase alignment is performed. Since order of phrases in sentences can be different in various languages, all possible alignments are considered and their occurrence throughout the corpus is marked. The obtained data is then used for the process of encoding and decoding, in which the translation is generated. Again, multiple translation options are considered and their probability is evaluated to choose optimal result of a translated sentence (Jurafsky & Martin, 2009).

The name phrase-based translation is sometimes used for SMT. The advantage of working whole phrases and their translations instead of individual words and transfer rules, as is the case of CMT, is the ability of SMT to easily consider collocations of words and their immediate context (surrounding words). A word can be translated differently in a phrase than when it occurs separately. SMT can easily identify such cases and provide an appropriate translation.

This approach is said to produce a compromise between faithfulness and fluency, similarly as what translators do in practice, because it in fact uses human translation

solution as its guide (Jurafsky & Martin, 2009). It can more successfully translate phrases, idiomatic expressions, metaphors and some culture-specific content. On the other hand, its problem is the same as with all statistical models – it is only an approximation of reality and a probability; the most likely translation is searched for, not the correct one. The generative ability of this approach is confined by the translations that have already been produced by humans. Infrequent or new phrases will be generated less accurately and in poorer quality, possibly worse than in case of CMT. Obviously, the quality of statistical MT highly depends on the size of the corpus. It cannot be used in fields where insufficient data is available.

Nonetheless, a corpus can be easily extended with new data and new algorithms for alignment and new calculation of probability can be added. More sophisticated methods of learning and decoding are mostly limited by computational abilities of computers and their memory – with improvement in those capabilities more powerful statistical MT engines can be created (Trujillo, 2012).

5.3 Neural Machine Translation

The most contemporary MT approaches use neural networks for their operation. The basic principle of neural machine translation is the same as in statistical machine translation and it originally served only as its supplement to improve performance. Only in the last few years has it been proposed as a stand-alone approach (Britz, Goldie, Luong & Le, 2017), and it quickly gained its prominence and became developed in a larger extent. A simple search query for recent papers on “machine translation” in databases with academic texts shows that neural machine translation can be found quite often. In *Findings of the 2016 Conference on Machine Translation (WMT16)* (Bojar et al., 2016), many of the compared MT engines also use neural networks, though the distinction is difficult, because multiple approaches are often combined together to produce optimal results. The most common publicly available MT engines, Google Translate (Turovsky, 2016) and Bing Translator ("Microsoft Translator is now powering all speech translation through state-of-the-art neural networks", 2016.), as well as more commercially oriented Systran ("Round-trip translation: no more entertainment with PNMT™ systems", 2016), all started to use the NMT methods at the end of the year 2016.

Because of its specific character, distinctive from the common SMT, and because of its actual importance and prospective possibilities, this chapter is devoted to NMT.

First, the basic principle of neural networks is described and the second part of the chapter focuses on the properties of NMT itself and compares it to the approaches mentioned previously.

5.3.1 Principle of Neural Networks

Artificial neural networks, sometimes also called connectionist networks are a specific AI method, which tries to replicate operation of neurons of the human brain. A network consists of number of nodes (which can be only in order of several decades up to several thousands) which are analogous to individual neurons in brain (Rojas, 2013). Each node performs specific calculation or processes signal based on its designed function. The parallelly arranged nodes are interconnected with connections (hence the name "connectionist networks") analogous to the connection of axons to dendrites via synapses. Connection *weights* are an important property of neural networks; they are numerical values representing the strength of individual connections, which determine whether signal from previous node will be processed and how much importance will be given to it. Therefore, they represent memory of a network since (after learning) they contain information about which features of the input are interrelated (ibid). *Figure 3* shows a basic organization of neural network. The specific functions of individual nodes and their arrangement depends on the design and purpose of the network.

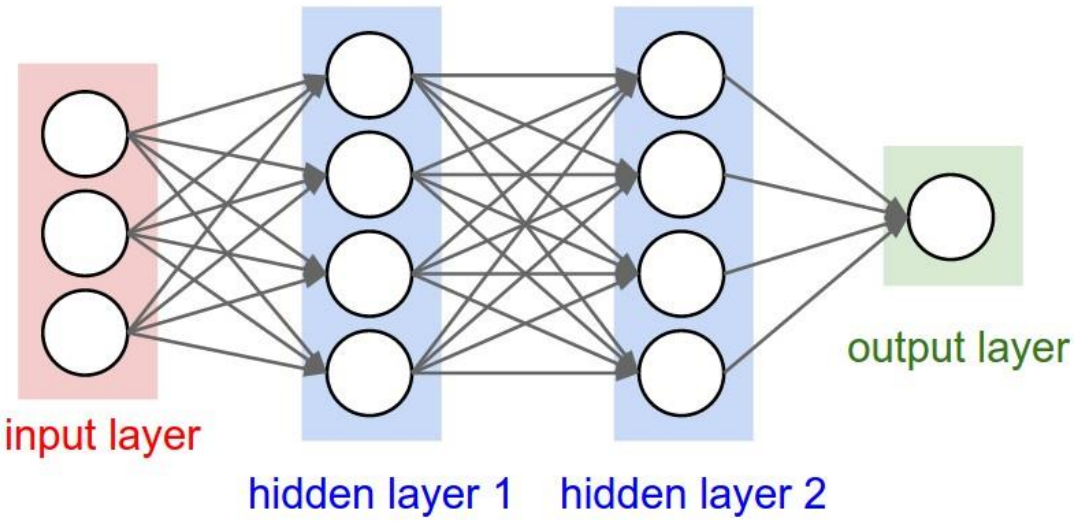

Figure 3 A Simple Feedforward Neural Network Interconnection (from CS231n Convolutional Neural Networks for Visual Recognition, n.d.)

In pattern recognition, machine translation and other language-related tasks, several basic layers of architecture can be distinguished - input nodes, so-called “hidden” nodes, and output nodes. The layer of hidden nodes can be further separated into multiple sub-layers. Each node is consequently responsible for processing certain feature of the input. The layers closer to the input process more general features and we move towards the output, the focus of the layers is more specific (Ekbia, 2008).

In the initial phase of creating models for pattern recognition tasks, the weights of connections are set randomly. Then there follows the learning phase, which can be either supervised or unsupervised. In supervised learning, the network is fed an input, which it processes and compares its own output with the right reference output, which is provided to the network as well. The network then tries to adjust its connection weights to match its output with the reference one. In the unsupervised learning, the network learns to recognize certain repeating patterns of the input (e.g. shapes, strings of letters or words, or identical translations of phrases in bilingual corpus) and it creates internal categories of co-related stimuli by adjusting the weights (Ripley, 1996). With each repetition, the approximation or prediction improves, until, usually after several hundred cycles, a certain level of saturation is reached and weights change only slightly.

It can be seen that the performance of the network is not directly influenced by the designer, who would set explicit instructions and rules. We do not need to know the exact mathematical function of the process or have a specific logic defined, instead we leave the network to create the optimal solution on its own by learning and self-organization. This principle of operation is however somewhat problematic, because it cannot be directly observed and modified. In other words, a neural network performs well, but we cannot exactly see why, and generalize the findings. Sometimes, a behavior of a neural network cannot be replicated, because each learning process is individual (Ekbia, 2008).

The non-deterministic nature of the neural networks makes them suitable for tasks, where no exact algorithmic solution can be found. They therefore fare well in pattern recognition, eg. recognition of objects in images, or in decoding of hand-written text, and in language processing tasks in general.

5.3.2 Operation of Neural Machine Translation

Most neural machine translation systems in fact utilize two neural networks. One works as *encoder*, which processes a SL input and generates its representation in the form of attention vector, which is then fed to *decoder* which is responsible for generating the TL output from the vector. Usually, the type of architecture used for the MT is called *recurrent neural network* in which, unlike in basic *feedforward* architectures demonstrated in *Figure 3*, the state of individual nodes can influence other parallel nodes and also nodes from previous sub-layers since connections can be bidirectional. This way the information that has already been processed, as well as the information that is at some lower stage of processing (closer to the input), can influence decisions of the nodes, and therefore, past and future input and output can be considered (Britz, Goldie, Luong & Le, 2017). *Figure 4* shows a basic connection of encoder-decoder NMT.

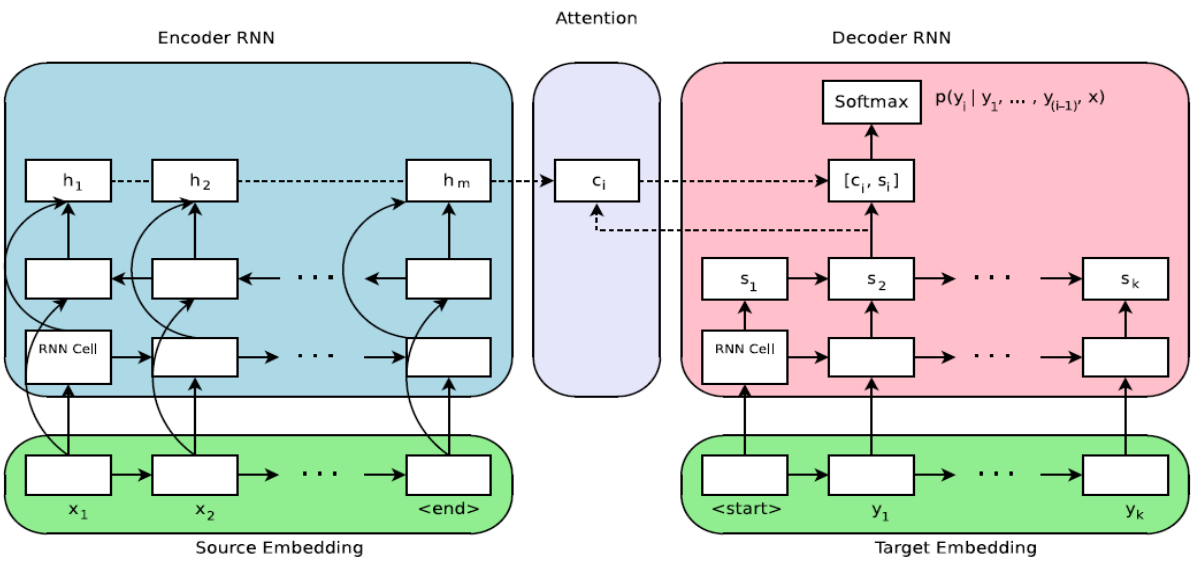

Figure 4 Encoder-decoder NMT Architecture (Britz, Goldie, Luong & Le, 2017)

When the first NMT models were introduced, they quickly displayed equivalent or better performance than SMT models which have been gathering data for about 10 years ((Cho, van Merriënboer, Bahadanau & Benigo, 2014; Britz, Goldie, Luong & Le, 2017). Cho et al. furthermore claim that size of a trained NMT engine can be only about 500MB, while common SMT engines require tens of gigabytes of memory (Cho, van Merriënboer, Bahadanau & Benigo, 2014). My practical experience with Edinburgh Neural Machine Translation Systems (Sennrich, Haddow & Birch, 2016) showed that a

trained model for unidirectional translation has size of about 5 GB, but its size is still comparably smaller than that of SMT engines.

The main disadvantages of NMT is the large learning time required for the model to be operational (in order of days or weeks), and the inability to exactly determine, why is a certain NMT engine operating efficiently or not. The methods for improving neural networks are usually done by changing various parameters, while the resulting quality is not known in advance, and with every change of parameters of an NMT model, the learning phase must start anew (Britz, Goldie, Luong & Le, 2017). Those limitations are reduced by increasing computational power, which is be one of the reasons that made NMT possible.

As was already mentioned, the neural MT is based on the principles of statistical MT. For both there is an underlying idea of statistical distribution of words in language, which implies that same or similar words/sentences/paragraphs will be translated similarly in multiple texts, and both require bilingual corpora as a reference for its operation. However, thanks to the characteristic behavior of neural networks, different computational methods are used in those approaches. The NMT seems to be more flexible in its ability to learn, adapt and recognize patterns on its own.

There exists a significant advantage of NMT, which, while it has not yet been fully developed, might lead to further improvement of quality of translation above the sentence level. As the NMT is able to search for patterns on its own – it is not pre-programmed what to look for, it might theoretically recognize features of a larger pieces of text (not only of a sentence or a part of a sentence). For example, repeated presence of specific terms or frequency of personal pronouns could help the NMT to indirectly determine style of a text and translate it accordingly. A different level of formality will be present in a lecture and in an email conversation, for example, and if an NMT engine recognizes with which type of text it is dealing with from the present patterns, it can use relevant vocabulary. However, the focus of contemporary MT systems is usually only one sentence while translating and also during consequent evaluation (Bojar et al., 2016). Considering greater-than-sentence-level features of text can be result of future development.

The inspiration with operation of neurons in brain, which the neural networks employ, might suggest that the NMT is closest to the procedures of human translators. A

closer examination however shows, that the NMT method appears to be considerably different. In the first place, there are two interconnected neural networks used, not only one as in the brain. The NMT also does not inherently understand the meaning nor does it perform any broader decisions about the text. It is simply a very successful method of searching patterns of translation, and same as the original SMT, the NMT is confined by what has already been translated by humans before. Finding advice in previous translations might be part of human translator's activity, but it most likely does not compose the whole process of translation. Though there is certain analogy with the human brain, the application of neural networks does not, in general, try to replicate the brain, and the neural networks are often used simply for their desirable computing capabilities.

The process of human translation rather resembles the methods of CMT, where certain analysis of the text to be translated is made with the knowledge of SL, and then, with the knowledge of TL rules and vocabulary, translated text is generated. The approach of NMT might more closely resemble the case of a person growing up in a bilingual environment, who somewhat more intuitively knows how to express same things in both languages, nonetheless, this analogy is far from perfect since NMT lacks mental representations and references to reality which the person has.

Even though the NMT provides a high quality of translation, it does not follow the procedures of human translators nor does it is employ some very complex AI capabilities that would allow it to understand text and make broader decisions. Still, it represents a very efficient method of translation, that is likely to be further developed and applied for the tasks of MT.

6 Translation Evaluation

6.1 Evaluation Methods

For a human translator, the conditions are slightly different since he or she is not expected to make grammatical and lexical mistakes. If they occur, it is more likely due to some random error or because of improper understanding. In other words, the translator is expected to be able to produce a fluent, naturally-looking text without mistakes. It is

then evaluated how successfully a message is communicated and if appropriate linguistic means were chosen. The situation is different for MT since it can, in its present state, generate mistakes that a conscientious human translator should not produce.

There are several aspects according to which the success of translation can be evaluated. The basic two dimensions of evaluation are fidelity and fluency. Within the scale of fidelity, adequacy and informativeness are considered – whether information from source text is preserved and can be used effectively; fluency is represented clarity and naturalness of the language (Jurafsky & Martin, 2009). Sometimes, style is also rated in the evaluations, but it is often considered too subjective and of no importance for MT (Fiederer & O'Brien, 2009). However, style should be definitely taken into account in the future if the computers are ever able to produce human-quality translation. Evaluation of fidelity, fluency, and style requires (preferably) multiple human readers and pre-defined scales, along which the text is rated. Such method is rather subjective and quite time consuming. Another, probably more objective, evaluation can be made by examining how much time is required for post-editing by a human corrector or how many changes have to be made (Jurafsky & Martin, 2009).

There are also automatic methods to evaluate the quality of translation. Most of them need multiple human translations of the same text as a reference and then they compare an output of MT with the human translations. They compute the "translation closeness," which is a metric representing the similarity between human translation and MT. The most common automated evaluation method is called BLEU (Jurafsky & Martin, 2009). The automatic methods usually do not provide information about overall quality of the MT engine in general; they find their use especially while comparing several MT systems with similar architectures to see which one provides the highest quality output, or while adding a new feature or module to existing MT system to see whether the quality has improved.

From a linguistic point of view, I believe there can be another how to evaluate products of MT. Various lexical, syntactic and semantic problems and phenomena can be considered and examined throughout a text. Evaluation would be based on how correctly are those problems solved. We can evaluate for example word order of individual phrases and whole sentences, case, tense, or whether a correct term is used. While other methods generally take text as a whole and rate overall quality, readability

and understandability, the suggested approach would provide us with the specific shortcomings of MT systems. It can then serve as another criterion of evaluation, especially useful when aiming for features which should be improved. Similar approach is used in the practical examples in the following section.

6.2 Practical Examples

I have used the Google Translate, probably the most widely used and accessible MT engine, to demonstrate the contemporary quality of MT. It uses the neural networks approach, which has been introduced only recently for English – Czech translations (Kasík, 20 April 2017). The CS-EN combination is listed under languages supported by the neural model in Google Translate documentation (*Language Support*, Google, 2017). It should therefore reflect the current trends in MT, while at the same time, it provides well-tested methods with quality that should be sufficient for end-users.

Following types of texts have been chosen for evaluation:

- News
- Manual
- Prose

In the texts, I will evaluate present morphological and syntactical mistakes, the vocabulary used and translation of terms and longer phrases, and, as a last instance, general understandability. The purpose of this evaluation is not a deep analysis of mistakes of MT systems, it only aims to provide several examples and insight into the level of overall quality that can be expected. Only those mistakes that are the most frequent, significant, or demonstrate well the behavior of the MT system are therefore commented upon while others might be disregarded.

The original texts and their translated counterparts can be found in *10 Appendixes*. The parts that are commented upon in the following sections are highlighted in **bold** for better reference.

6.2.1 News

See *10.1 Appendix 1: News*.

News has been chosen as they represent a situation in which a common user might want to have an article from a news website written in another language translated. They

can be easily accessed, there is demand for them to be available quickly, and the information contained is the most important feature, so user can prefer fast lower-quality translation over a high-quality translation, which would be provided with delay. For the news translation, a recent text concerning politics of the USA has been chosen (Diamond and Jarret, 18 May 2017).

As can be seen, the translator is quite successful regarding the choice of cases and word order; it can well recognize parts of sentence and choose appropriate word form.

Sometimes, the engine is able to perform some more complex reordering, e.g. … *campaign adviser and surrogate* : *poradce a náhradník kampaně*; *(i)n a statement, Trump said …* : *Trump uvedl ve svém prohlášení ….*

There are also some errors in the choice of tense, e.g. *The Justice Department on Wednesday appointed former FBI Director Robert Mueller as special counsel to oversee the federal investigation* : *Ministerstvo spravedlnosti ve středu jmenovalo bývalého ředitele FBI Roberta Muellera za zvláštního právního zástupce, který dohlížel na federální vyšetřování.*

As for vocabulary, the errors or inappropriate translations are more frequent. Consider for example the title of the news: *Special counsel appointed in Russia probe : Zvláštní právník jmenovaný v ruské sondě.* More appropriate translation would probably be "*Zvláštní vyšetřovatel ustanoven v ruské kauze,*" while a Czech reader might also require an explicit description of what is meant by *Russia probe*, which is one of translator's decisions that MT does not perform. The term *counsel* is translated multiple times differently throughout the text – this might be a problematic feature of NMT, as it is very sensitive to every individual use of a word, but this behavior reduces consistency of translation.

Other errors in the vocabulary used can be seen for example in *Trump fired FBI Director* : *Trump vystřelil ředitel FBI*;. Property of neural machine translators should be the ability to derive from a phrase, which meaning of a word is intended, but it fails in those cases. Here, the word *fire* is used in the metaphorical sense as "*make somebody redunandt,"* and it should be translated as "*propustit*". It would probably be obvious to any human translator from the context since both subject and object of the verb are persons. The NMT engine is clearly not capable of such understanding and it was unable to associate the right translation for the phrase.

In another error in the vocabulary: *between President Donald Trump's campaign associates* : *mezi kamarády prezidenta Donalda Trumpa;* the translator chose wrong translation for the word *associate*. In the context of presidential campaign, the associates are not *kamarádi*, but more likely "*společníci; partneři,"* which the translator was unable to recognize. It closely resembles a situation, in which the translator would be unable to use appropriate register, which might also be a problem for general application.

On the other hand, the MT engine is able to successfully deal with some specific terms such as *collusion* : *tajná dohoda* ; *Deputy Attorney General* : *Zástupce generálního prokurátora*.

A very serious mistake also is that the system did not translated part of the sentence: *In the meantime, I will never stop fighting for the people and the issues that matter most to the future of our country*. : *Lidem a otázkám, které jsou pro budoucnost naší země nejdůležitější*. Without the beginning, the sentence does not make sense, and the reason why the MT system decided to omit it is unclear. It is rather a design mistake, than an intended behavior, but it again demonstrates certain unpredictability and our inability to directly influence the behavior of neural networks.

Due to numerous mistakes, some parts of the output text do not look natural and it is still obvious that the translation was performed by MT. The general message of the news can be understood, but some unclear passages and words (e.g. the translation of *counsel*) might require the reader to compare both texts and search some terms manually in a dictionary.

6.2.2 Manual

See *10.2 Appendix 2: Manual*.

Manual might be relevant for the common user as well, but it is most beneficial for companies where the use of automated translation into multiple languages for product documentation can increase the speed of translation and significantly decrease its cost. An excerpt from a user manual for Sony camera was used (Sony User Guide: DSC-H2/H5 User Guide, 2006, p. 7)

Except for the wrong case of the word *baterie* in the first sentence (*Notes on the Nickel-Metal Hydride battery* : *Poznámky k nikl-metal hydridové baterie*, there are no grammatic or syntactic mistakes in the text.

It can be seen that the MT engine can extend some terms to make them more clear in CS, e.g. *supplied* : *je součástí dodávky* (even though "*je součástí balení"* would probably be better). It can also successfully distinguish between various uses of name *Carl Zeiss;* compare: *Carl Zeiss lens* : *Objektiv Carl Zeiss* and *quality assurance system certified by Carl Zeiss : v rámci systému zabezpečování jakosti certifikovaného společností Carl Zeiss*.

The translated text looks rather natural except for the part *If you do not intend to use the batteries for a long time* : *Pokud nemáte v úmyslu využít baterie delší dobu*, where inversion might be suitable ("*Pokud hodláte baterie delší dobu nevyužívat,*" for example). However, naturalness is not as an important property of technical texts. The message can be well understood and only with minor modifications, the text could be used.

The most significant difference in the original translation into Czech (Sony Uživatelská příručka: DSC-H2/H5, 2006, p. 127) are differently translated terms: *nikl-metal-hydridový akumulátor* and *systém kontroly kvality*, but these differences can easily be resolved manually, or, if specific NMT engine is used, it can be taught to prefer desired terminology.

6.2.3 Prose

See *10.3 Appendix 3: Prose*.

The use MT for literary texts is not common, but its possible application is not completely disregarded in research (Voight & Jurafsky, 2012). It has been included here to display some limitations that the MT has in literary translations, but also demonstrate the opposite direction of translation, CS-EN. Part of *Nesnesitelná lehkost bytí* by Milan Kundera was chosen (Kundera, 2006) as it represents a relatively modern Czech text with no special or archaic language, while it includes reflections and some figurative language.

Again, there are not many mistakes regarding the word order, tenses or forms of words. Thanks to the focus on whole phrases it translates for example *Usnula : She fell asleep* quite easily. Probably the most serious mistake is the frequent interchange of *he* and *she*, e.g. *Bál se té odpovědnosti. Kdyby ji teď k sobě pozval, přijela by za ním, aby mu nabídla celý svůj život. : He was afraid of that responsibility. If she had invited her now, she would come to him to offer her all her life.* This issue is even more problematic, as the form of verbs (*pozval*) and pronouns(*mu*) in CS clearly suggests that the masculine gender should be used. This behavior is specific for the NMT approach, in which we

cannot exactly determine, why it decided to use pronoun *she*; such mistake would probably not happen in CMT engines, or we should be able to fix it.

The translation of the figurative phrase, which can occur especially in literary texts is also worth mentioning: *dítě, které někdo položil do ošatky vytřené smolou a poslal po vodě řeky, aby ji Tomáš vylovil na břeh své postele* : *a child that had been laid in a battered rag and sent by the river to Tomas to be taken to the bed of his bed*; which then repeats in *dítě, které vytáhl z ošatky vytřené smolou a položil na břeh své postele* : *a child he had pulled out of a ragged rack and laid his bed on the bank*. In the translation by Michael Henry Heim (Kundera 1984) the same passage reads as follows: *a child someone had put in a bulrush basket daubed with pitch and sent downstream for Tomas to fetch at the riverbank of his bed* and then *a child whom he had taken from a bulrush basket that had been daubed with pitch and sent to the riverbank of his bed*. The first obvious problem is the translation of *ošatka vytřená smolou*, where it is again unclear, why the engine chose the used translations. The second problem is that the repetition that was likely intentional in the original text, and it is maintained in the translation by Heim, but it is not preserved by the MT. It again shows that the engine is unable to maintain consistency and a slight change in the sentence can result in a completely different translation.

While the text is fluent in most parts, many mistakes reduce its understandability, and some poor vocabulary choices decrease the overall quality of the translation. The plot itself could be understood, but only with difficulties, which reduces impact of aesthetic aspects and atmosphere of the text, which are, however of major importance in literary texts.

7 Application of Machine Translation

As was mentioned in the introduction, no Fully Automatic High-Quality Translation MT system exists to this day that would be applicable to translation. The practical examples of from previous chapter show that NMT, which is considered state-of-the-art technology, can cope with some language differences, such as word order, and inflection; it is sometimes successful in identifying and translating terms and phrases, but still produces numerous mistakes mostly on the sematic level. Furthermore, it displays inconsistency in its translation and it behavior cannot be fully predicted and influenced.

In general, the translation engines still produce various mistakes and their use is limited either by range of its applicability or by resulting quality. Jurafsky & Martin distinguish following tasks which can be addressed by current computational models:

- task for which rough translation is adequate,
- task which are later post-edited by a human,
- task limited to small sublanguage (2009).

Another alternative is to use pre-editing and of Controlled Language to prepare an input which can be easily processed by MT system.

7.1 Rough Translation

Rough (sometimes also "raw") translation denotes pure output of an MT system, without any editing. Example of use of rough translation can be the use of online MT engines to translate news, as in the previous chapter, where message can be, with some difficulties, understood. Such application is facilitated by contemporary internet browsers, which offer automated translation of foreign websites – such a feature can be found in Google Chrome or in Seznam.cz Browser, for instance. The output quality is not very high, but it allows a user with only poor or no knowledge of the source language to understand the basic idea of the text.

Even more progressive approach is taken in Play Store, Google software a media download manager of Android operating system. Here, basic application descriptions are automatically translated into user's native language (determined by his settings and location) and there is no direct method to disable this. It demonstrates the confidence that Google has in their translations, and that the company finds the translation adequate and more convenient for a user than reading the description in the source language. It should be noted though, that it is often hard to infer meaning from the results of Play Store translations. The descriptions use advertising language, which is in these cases not translated sucesfully, so this is, in my opinion, an unsuccessful application of MT, at least for English-Czech language pair. It can be demonstrated by following translations that can be found in Play Store: *Drive tak rychle, jak je to možné, ale nepatří!* (Vertigo Racing); *Zrušte desku. Platit to, co chcete. Dobře?* (Okay?); *Nyní možnost nejen zaklepat. To také pošle oznámení.* (LinkedIn Job Search).

However, if we combine the skopos theory, focus of which is purpose of translation, with speed, convenience and low cost of MT, and also with the fact that translation can be initiated by a reader who has no knowledge of SL, we can find a raw MT translation an acceptable output. When the MT output is appropriate to help reader understand the basic content, he or she can afterwards decide to have the original text translated, or the raw translation post-edited.

7.2 Editing and Sublanguages

Sometimes, various levels of human and computer involvement are considered within translation, from classic human translation with no use of computer to a full MT with no human interference. For stages between these two extreme positions, terms *Machine-Aided Human Translation* (MAHT) and *Human-aided Machine Translation* (HAMT) are used, though the boundaries are often uncertain (Hutchins & Somers, 1992).

Post-editing includes a human editor who corrects mistakes in the raw translation and possibly makes certain improvements towards naturalness. This can somewhat speed-up a translation process compared to human translations. Additionally, the editor does not have to possess as good language skills as a translator; in case of higher quality of raw MT output, editor might theoretically have no or only little knowledge of the source language. In some cases, the NMT from the practical application seemed to be able to translate more complex or infrequent terms efficiently and this might reduce the time of searching for the right term by human translator. In many other cases, however, the editor would have to correct the wrong terms of raw trasnlation. A research on quality of MT had also shown, that post-edited sentences were rated as more accurate and clear than sole human translations. On the other hand, human translations scored better in style and were in general chosen as better ("favorite") ones in the research (Fiederer & O'Brien, 2009). All translated sentences were of technical character, which supports the idea of using MT mainly for non-literary texts.

The Google Translate also offers several possible variants for each translated sentence, and the user can choose the most suitable one. The alternatives can be displayed by hoovering the mouse over the translated sentence. This functionality can also be considered as an example of post-editing.

Pre-editing and use of Controlled Language involves adjustments before a text is processed by an MT system. During pre-editing phase, phrases and their dependencies can be marked in text by human more accurately than with use of automatic parser, and translation of terminology can be defined in advance. Use of Controlled Language is used when it is known in advance that a text will be translated by an MT system. It requires following certain rules during text production and avoiding so-called *Negative Translatability Indicators* – for example sentences over 25 words, passive voice, gerunds, longer noun phrases, etc. (Fiederer & O'Brien, 2009). Both pre-editing and use of controlled approach is advantageous especially when text is to be translated into multiple languages.

Application of MT in a sublanguage also includes working with the Controlled Language, since it means limitation only to several types of phrases and certain vocabulary. With these limitations, the interlingua approach can be employed efficiently. Examples of sublanguage can be weather forecast, hotel reservations, equipment maintenance manuals, meeting scheduling, etc., where FAHQT can be achieved (Jurafsky & Martin, 2009). As can be seen, however, the sublanguage domains are often very narrow, and high quality of translation is due to translatability of the information source, rather than due to a good MT engine. Still, this system can be suitable for technical manuals and guides, or for legal and bureaucratic documents of multilingual bodies, such as European Union, where style is of lesser importance and it might be required to translate large amount of content into multiple languages.

Indeed, it is common to be designing the MT system for a specific purpose, rather than for general use. It is often suggested in books about MT systems, that a developer should consider the purpose of his MT engine and make choice about rules and translation methods, which will be necessary (Hutchins, Sommers, 1992; Trujillo, 2012). The purpose of an MT system may not be as narrowed down as in the case of very specific sublanguages mentioned previously, but not all possible rules and entire vocabulary always has to be covered. A dictionary can be limited to include only the required terminology, which will be used within the given field, which also improves the consistency of used terms in the translation (Trujillo, 2012).

SMT and NMT methods can be used conveniently in this case, provided that there is a corpus of the given field large enough for prior learning. Alternatively, a general-

purpose MT such as Google Translate, can be augmented with domain-specific data to improve performance within given field (Clark, Lavie & Dyer, 2012). The operation of NMT should be beneficial in such specific applications thanks to the advanced ability of neural networks to learn, where not only the prior choice of corpus, but also the consequent post-editing can gradually improve the translation quality. An example of a field, for which MT system are commonly adapted is medicine, as show following researches: (Dušek et al., 2014; Lu et al., 2014; Urešová et al., 2014).

8 Conclusion

It appears that language is a complex phenomenon which, despite many efforts, has not been fully formalized into rules allowing complete computational processing due to a very complex nature of language phenomena and because of extralinguistic features coming into play. A universal translation system capable of producing FAHQT would probably have to reach the level of complete AI in order to overcome all possible problems and reach the quality of human translators. Computers usually process only individual sentences and cannot take context and larger picture into account. There is always some level of ambiguity between multiple languages, and one-to-one correspondence of words cannot be ensured, and this makes choice of proper translation terms complicated for computers, because they lack natural understanding of meaning. While CMT is superior in addressing specific grammatical differences between languages and enable direct control over the translation, SMT and NMT can perform better when addressing ambiguous terms and phrases, since it uses prior human translations as a template, and they are the most developed approaches.

While the NMT, the most recent and widely used method, uses human brain as its inspiration, it does not aim to replicate the process of human translator. Instead, it uses neural network for efficient pattern recognition. The resulting output contains mistakes which usually reveal that the translation is product of MT, but the rough translation can be adequate to understand the general message of the text and sometimes only minor modification is required. The main disadvantage is their complicated design requiring large computational power for training, and the fact that their behavior cannot be directly observed and influenced, which also produces some specific mistakes that are hard to be prevented.

Obviously, contemporary application of MT always requires a compromise. We either have to settle for a lower quality of the output, or we have to design and use an MT system solely for a limited range of purposes. However, if an adequate MT system is chosen with regards to requirements, it can definitely be beneficial compared to using of services of classic human translator because of its speed and lower cost. In foreseen future, the MT will not replace human translators. More likely the computers and humans will be more cooperating in HAMT and MAHT, improving the efficiency of translations in general. MT is also mostly applicable for non-literary genres, while literary translations still remains a human domain.

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10 Appendixes

10.1 Appendix 1: News

Diamond, J. & Jarret, L. (20 May 2017) Special counsel appointed in Russia probe. CNN.com. Retrieved from http://edition.cnn.com/2017/05/17/politics/special-counsel-robert-mueller/index.html

Special counsel appointed in Russia probe Washington (CNN) **The Justice Department on Wednesday appointed former FBI Director Robert Mueller as special counsel to oversee the federal investigation** into Russian interference in the 2016 election, including potential **collusion** between **President Donald Trump's campaign associates** and Russian officials. **Deputy Attorney General** Rod Rosenstein appointed Mueller to the position in a letter obtained by CNN. Attorney General Jeff Sessions previously recused himself from any involvement in the Russia investigation due to his role as a prominent campaign adviser and surrogate. READ: Rosenstein letter appointing Mueller special **counsel** As **special counsel**, Mueller is "authorized to prosecute federal crimes arising from the investigation of these matters," according to the Justice Department order Rosenstein signed. Mueller's appointment aims to quell the wave of criticism that Trump and his administration have faced since **Trump fired FBI Director** James Comey last week in the middle of the FBI's intensifying investigation into contacts between Trump campaign associates and Russian officials. In a statement, Trump said an investigation will confirm that "there was no collusion" between his campaign and Russia.	***Zvláštní právník jmenovaný v ruské sondě*** Washington (CNN) **Ministerstvo spravedlnosti ve středu jmenovalo bývalého ředitele FBI Roberta Muellera za zvláštního právního zástupce, který dohlížel na federální vyšetřování** ruských zásahů do voleb do roku 2016, včetně případné **tajné dohody** mezi **kamarády prezidenta Donalda Trumpa** a ruskými úředníky. **Zástupce generálního prokurátora** Rod Rosenstein jmenoval Muellera na pozici v dopise získaném CNN. Generální prokurátor Jeff Sessions se předtím odvolal z jakékoli účasti v ruském vyšetřování kvůli své úloze významného poradce a náhradníka kampaně. ČTĚTE: Rosensteinův dopis, kterým jmenuje Muellera zvláštní radu Jako **zvláštní poradce** je Mueller "oprávněn stíhat federální trestné činy vyplývající z vyšetřování těchto záležitostí", podle rozkazu ministerstva spravedlnosti Rosensteina podepsal. Muellerovým jmenováním se snaží potlačit vlnu kritiky, kterou Trump a jeho administrativa čelili, když **Trump vystřelil ředitel FBI** Jamese Comeyho minulý týden uprostřed zintenzivnění vyšetřování FBI ohledně kontaktů mezi kamarády z kampaně Trump a ruskými úředníky. Trump uvedl ve svém prohlášení, že vyšetřování potvrdí, že mezi jeho kampaní a Ruskem nebyla žádná tajná dohoda.

"As I have stated many times, a thorough investigation will confirm what we already know -- there was no collusion between my campaign and any foreign entity. I look forward to this matter concluding quickly. **In the meantime, I will never stop fighting for the people and the issues that matter most to the future of our country**." In a brief statement, Mueller said, "I accept this responsibility and will discharge it to the best of my ability."	"Jak jsem již mnohokrát uvedl, důkladné vyšetřování potvrdí to, co už víme - nebyla žádná tajná dohoda mezi mé kampaně a žádnou zahraniční entitou. Těším se, že se tato záležitost rychle uzavře**. Lidem a otázkám, které jsou pro budoucnost naší země nejdůležitější**. " V krátkém prohlášení Mueller řekl: "Přijmu tuto zodpovědnost a udělám to podle mého nejlepšího výkonu."

10.2 Appendix 2: Manual

Sony. (2006). User's Guide/Troubleshooting: DSC-H2/H5. Retrieved from https://www.sony.co.uk/electronics/support/res/manuals/2673/26731761M.pdf (p. 7)

Notes on the Nickel-Metal Hydride battery Charge both of ne Ni-HM batteries (**supplied**) before using the camera for the first time. (→ step 1 in "Read This First") The batteries can be charged even if they are not completely discharged. Also, even if batteries are not fully charged, you can use the partially charged capacity of the battery as is. **If you do not intend to use the batteries for a long time**, use up the existing charge and remove them from your camera, then store them in a cool, dry place. This is to maintain the batteries' function (page 110). For details on the usable batteries see page 110. **Carl Zeiss lens** This camera is equipped with a **Carl Zeiss lens** which is capable of reproducing sharp images with excellent contrast. The lens for this camera has been produced under **quality assurance system certified by Carl Zeiss** in accordance with the quality standards of **Carl Zeiss** in Germany.	**Poznámky k nikl-metal hydridové baterie** Nabijte obě Ni-HM baterie (**je součástí dodávky**) před prvním použitím fotoaparátu. (→ krok 1 v části "Nejdříve si přečtěte") Baterie lze nabíjet i v případě, že nejsou zcela vybité. I když nejsou baterie plně nabité, můžete použít částečně nabitou kapacitu baterie. **Pokud nemáte v úmyslu využít baterie delší dobu**, vybijte akumulátory a vyjměte je z fotoaparátu, poté je uložte na chladném a suchém místě. Tím je zachována funkce baterií (strana 110). Podrobnosti o použitelných bateriích viz strana 110. **Objektiv Carl Zeiss** Tento fotoaparát je vybaven **objektivem Carl Zeiss**, který dokáže reprodukovat ostrý obraz s vynikajícím kontrastem. Objektiv pro tento fotoaparát byl vyroben v rámci **systému zabezpečování jakosti certifikovaného společností Carl Zeiss** v souladu s normami kvality **společnosti Carl Zeiss** v Německu.

10.3 Appendix 3: Prose

Kundera, M. (2006). *Nesnesitelná lehkost bytí*. Brno: Atlantis.

Myslím na Tomáše už řadu let, ale teprve ve světle této úvahy jsem ho uviděl jasně. Viděl jsem ho, jak stojí u okna svého bytu a dívá se přes dvůr na zdi protějšího činžáku a neví, co má dělat.	I have been thinking about Tomas for many years, but I have seen it clearly in the light of this reasoning. I saw him standing at the window of his apartment, looking over the courtyard on the wall of the opposite apartment, and not knowing what to do.
Potkal Terezu poprvé asi před třemi týdny v jednom malém českém městě. Byli spolu sotva hodinu. Doprovázela ho na nádraží a čekala s ním až do chvíle, kdy nasedl do vlaku. O deset dnů později přijela za ním do Prahy. Milovali se spolu ještě téhož dne. V noci dostala horečku a zůstala, pak celý týden s chřipkou v jeho bytě.	He met Tereza for the first time about three weeks ago in a small Czech town. They were barely an hour together. She escorted him to the station and waited until he got on the train. Ten days later she came to Prague. They loved each other the same day. At night, she got a fever and stayed, then a whole week flu with his apartment.
Pocítil tehdy nevysvětlitelnou lásku k té téměř neznámé dívce; zdálo se mu, že je to **dítě, které někdo položil do ošatky vytřené smolou a poslal po vodě řeky, aby ji Tomáš vylovil na břeh své postele**. Zůstala u něho týden, než se uzdravila, a pak zase odjela do svého města vzdáleného dvě stě kilometrů od Prahy. A tehdy přišla ta chvíle, o které jsem mluvil a která mi připadá jako klíč k jeho životu: stojí u okna, dívá se do dvora na zdi protějších činžáků a přemýšlí: Má ji pozvat do Prahy natrvalo? **Bál se té odpovědnosti. Kdyby ji teď k sobě pozval, přijela by za ním, aby mu nabídla celý svůj život**.	He felt an inexplicable love for the almost unknown girl; It seemed to him that he was **a child that had been laid in a battered rag and sent by the river to Tomas to be taken to the bed of his bed**. She stayed with him for a week before she recovered, then went back to her town, two hundred miles from Prague. And then came the moment I talked about as a key to his life: he stands by the window, looks into the courtyard on the walls of the opposite apartment, and thinks: Should he invite her to Prague permanently? **He was afraid of that responsibility. If she had invited her now, she would come to him to offer her all her life.**
Anebo se jí už nemá hlásit? To by znamenalo, že Tereza zůstane servírkou v restauraci jednoho zapadlého města a on ji už nikdy neuvidí.	Or should she no longer report it? That would mean that Tereza would remain a waitress in the restaurant of a dark city, and he would never see her again.
Chtěl, aby za ním přijela anebo nechtěl?	Did he want to come or not want him?
Díval se do dvora na protější zdi a hledal odpověď. Vzpomínal si znovu a znovu, jak ležela na jeho gauči; nepřipomínala mu nikoho z jeho předchozího života. Nebyla to ani milenka ani manželka. Bylo to **dítě, které vytáhl z ošatky vytřené smolou a položil na břeh své postele**. **Usnula**. Přiklekl k ní. Její horečnatý dech	He looked into the courtyard on the opposite wall, searching for the answer. He remembered again and again as she lay on his couch; Did not remind him of any of his previous life. She was neither a lover nor a wife. It was a **child he had pulled out of a ragged rack and laid his bed on the bank**. **She fell asleep**. He

se zrychlil a ozvalo se slabounké zaúpění. Při tiskl svou tvář k její a šeptal jí do spánku uklidňující slova. Po chvíli cítil, že se její dech klidní a její tvář se maně pozvedává k jeho tváři. Cítil z jejích úst jemný pach horečky a vdechoval ho, jako by se chtěl naplnit důvěrností jejího těla. A v té chvíli si představil, že je u něho už mnoho let a že umírá. Měl náhle jasný pocit, že by její smrt nepřežil. Položil by se vedle ní a chtěl by zemřít s ní. Pohnut tou představou, vtiskl v té chvíli tvář do polštáře vedle její hlavy a dlouho tak zůstal.	knelt to her. Her feverish breathing speeded up, and there was a faint sigh. He pressed his face to her and whispered to her sleeping reassuring words. After a moment, he felt her breathing calm and her face lifting her face to his cheek. He felt a fine smell of fever in her mouth, inhaling him as if he wanted to fill the confidentiality of her body. And at that moment he imagined he had been with him for many years, and that he was dying. He suddenly had a clear feeling that her death would not have survived. He would lay beside her and want to die with her. Moved by the imagination, he pressed his face into the pillow beside her head at that moment and stayed for a long time.