Morphological and Lexical Decomposition as a Basis for Identifying Multiword Expressions

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Abstract

A multi-word expression (MWE) is a construct of more than one orthographic word which possesses a single idiosyncratic meaning. MWEs, such as “hot dog”, “by and large”, “kick the bucket”, “spill the beans”, and “look up” are extremely prevalent in our vernacular. The identification of MWEs is important for many practical applications including translation and speech-to-text.

This work presents a method for improving the identification of MWEs using a concept termed Text Isolation. It focuses on dissecting (or “isolating”) the morphological properties of words in order to discover potential MWEs. Movie subtitle files are exploited in order to align the individual subtitles between different translations for each movie, thus generating a multi-lingual (Spanish-English-Hebrew) parallel corpus. After this subtitle-level alignment is performed, the Text Isolation technique is applied to the corpus. A word-level alignment algorithm is then used to acquire Hebrew MWEs and their translations. This method improves MWE identification in addition to improving the alignments to those MWEs.
Abbreviations and Notations

MWE — Multi-word expression
POS — Part of speech
API — Application programming interface
$C_E$ — Monolingual English corpus
$C_H$ — Monolingual Hebrew corpus
$C_S$ — Monolingual Spanish corpus
$C_{E,H}$ — Bilingual English-Hebrew corpus
$C_{S,H}$ — Bilingual Spanish-Hebrew corpus
$C_{E,S}$ — Bilingual English-Spanish corpus
$C_{I,E,H}$ — Isolated bilingual English-Hebrew corpus
$C_{I,S,H}$ — Isolated bilingual Spanish-Hebrew corpus
$C_{I,E,S}$ — Isolated bilingual English-Spanish corpus
$SEQ_{E,H}$ — Set of multi-token Hebrew sequences aligned in $C_{E,H}$
$SEQ_{S,H}$ — Set of multi-token Hebrew sequences aligned in $C_{S,H}$
$SEQ_{E,S}$ — Set of multi-token Hebrew sequences aligned in $C_{E,S}$
$SEQ_{I,E,H}$ — Set of multi-token Hebrew sequences aligned in $C_{I,E,H}$
$SEQ_{I,S,H}$ — Set of multi-token Hebrew sequences aligned in $C_{I,S,H}$
$SEQ_{I,E,S}$ — Set of multi-token Hebrew sequences aligned in $C_{I,E,S}$
$SEQ_{E,H} \cup SEQ_{S,H}$ — Set union of $SEQ_{E,H}$ and $SEQ_{S,H}$
Chapter 1

Introduction

1.1 Multiword expressions (MWEs)

Natural language is constructed from words each expressing some meaning. However, sometimes more than one word is required in order to convey a single semantic concept; the words interact to exhibit idiosyncratic behavior measurably higher than that of the constituents. The term compositionality refers to the semantic measure of the relationship between the meaning of a word sequence as a whole and the sum of its parts. As such, a multi-word expression (MWE) is a construction of more than one orthographic word whose meaning is idiosyncratic and cannot be inferred from that of its constituent words.

While some semantic concepts can be expressed either by a MWE or by a single word, others can be expressed only via a non-compositional MWE. The highly non-compositional MWE kick the bucket may be expressed with extreme compositionality as die. In contrast, the MWE Red Cross has no single-word equivalent. The spectrum of variations in compositional behavior is characteristic of all natural languages. The non-compositional Hebrew\footnote{To facilitate readability we use a transliteration of Hebrew using Roman characters; the letters used, in Hebrew lexicographic order, are abgdhwzxTlms'pcrst.} MWE bit spr (lit. “book house”), meaning “school”, is constructed from two lexemes. There are many differences in MWE construction between languages such as English and Hebrew whose morphological and syntactic properties vary greatly. These language-specific properties serve as the foundation of our research.
An all encompassing definition for MWEs has yet to be agreed upon. MWEs have been described as expressions consisting of two or more words that correspond to some conventional way of saying things (Manning and Schütze [25, Chapter 5]). This definition focuses on the usage of MWEs from a linguistic aspect. Other definitions focus on the frequency of occurrence; multiword expressions are sequences of words which co-occur at a highly statistical significance (Baldwin et al. [3]). Sag et al. [35] define MWEs as “idiosyncratic interpretations that cross word boundaries (or spaces)”, i.e. a MWE’s meaning is greater than the sum of the meanings of its constituent words.

Multiword expressions exhibit very diverse characteristics. These traits express themselves in the form of semantic, syntactic, and morphological properties. Semantically, the issue of compositionality, as noted by Bannard et al. [5], should not be addressed in black and white. The semantic behavior of MWEs may range from the barely non-compositional (e.g., “train station”) to the fully idiomatic (e.g., “kick the bucket”). Syntactically, some MWEs may appear as fixed patterns with unchangeable constituent order (e.g., “by and large”). Other MWEs allow for various levels of syntactic transformations on some or all of their constituent words who may even be subject to reorder. Morphologically, MWEs may allow some of their constituents to freely inflect while restricting the inflection of others (e.g., “get a kick out of something”).

In order to better understand the structure of MWEs, we will discuss the structure of words in general. Words are composed of morphemes. A morpheme is defined as the smallest unit of language with semantic meaning. A language’s morphology dictates how morphemes combine to create a word. Free morphemes may appear independently as words (e.g., dog, order) whereas bound morphemes may only be attached to a root or to other morphemes to form a word (e.g., dogs=dog+s, disorderly = dis+order+ly). In terms of morphemes, languages can be classified by where they fall on a continuum which represents morpheme-to-word ratio, and range from isolating (low ratio) to synthetic (high ratio). In comparison with other languages, English words have very few morphemes and therefore English is an isolating language. In contrast, Hebrew allows a higher number of morphemes to be attached as affixes to a word’s base lexeme. In that sense, Hebrew is more synthetic. Furthermore, attached morphemes may be inflected in addition
to the lexeme inflection, oftentimes dictating a change in the appearance of the lexeme to which they are conjoined. For example, in the word \textit{mtnk} (lit. “gift-your”), “your gift”, the suffixed possession morpheme inflected in the second person \((k)\) forces the lexeme \textit{mtnh} to transform its \textit{h} to \textit{t} to accommodate the attachment \((mtnh+k = mtnk)\).

Words may contain multiple morphemes but not all morphemes are necessary in order for a MWE to convey its intended semantic meaning. For example, the MWE \textit{kick the bucket} is the actual MWE and incorporates the bare minimum needed to express the concept of \textit{die}. Yet, when expressed as \textit{kicked the bucket}, the morpheme \textit{+ed} added to \textit{kick} only indicates the past tense form of the word but does not serve to generate a different interpretation of the MWE. In Hebrew, the search for the base MWE can be more complicated. The Hebrew excerpt \textit{wbbit hspr} (lit. “and in the school”) can be decomposed into the morpheme structure \textit{w+b+bit h+spr}, revealing the base MWE \textit{bit spr} (lit. “school”). We note that excess morphemes may even appear between constituent words, as evidenced by the morpheme \textit{h} (lit. “the”) expressing the determiner. The Hebrew determiner \textit{h} and conjunction \textit{w} (lit. “and”) are bound morphemes, and they always function as attached prefixes. Sometimes, these non-orthographic morphemes are necessary to the MWE. In the MWE \textit{m˘sa wmtn} (lit. “carrying and giving”), “negotiations”, the article morpheme \textit{w} is a necessary part of the MWE. On the other hand, as in the example \textit{bit hspr} (lit. “the school”) the determiner morpheme \textit{h} is optional.

For the purposes of this thesis, we define a multiword expression as a construct of more than one orthographic word whose constituents are the base forms of all the non-superfluous morphemes necessary to complete a single semantic understanding.

1.2 Motivation

There is an overwhelming prevalence of MWEs comprising any natural language. It has been estimated that the number of MWEs in a speakers’ lexicon is of the same order of magnitude as the number of single words (Jackendoff [19]). According to Sag et al. [35], who observed that 41\% of the entries in WordNet 1.7 (Fellbaum [14]) are MWEs, this is a gross underestimate. Erman and Warren [11] discovered that on average approximately
half of the texts which they considered were comprised of what they refer to as prefabricated language. They define these prefabs as multiword sequences which embody conventionalized ways of expressing concepts, preferable by native speakers over any other equivalent way of conveyance.

In recent years, there has been growing attention given to MWEs and their applications in natural language processing. In order to incorporate MWEs and to exploit their benefits, MWEs must be successfully identified and processed. MWE identification provides a foundation which strengthens the quality of a variety of NLP-related tasks, such as information retrieval, machine learning, statistical parsing, language generation, speech processing, word sense disambiguation, and lexicography.

Languages with complex morphologies pose a considerable challenge to the task of MWE identification. The rich morphology of such languages further compounds the problem of performing accurate lexical analysis of MWEs and obfuscates syntactic interpretation. Since each word (and MWE) may appear in many forms, each form will appear less times in a text, thus increasing data sparsity. Hebrew, which is the focus of our research, is one such example of a language with a rich and complex morphology. We further discuss the nature of Hebrew MWEs below.

1.3 Hebrew multiword expressions

In our work, we focus on the identification of Hebrew MWEs. The rich morphology and agglutinative properties of the Hebrew language pose a difficult challenge to the task of MWE identification. Hebrew MWEs, like those of other languages, can be characterized by a wide variety of linguistic properties. As such, we attempt to locate a commonality among Hebrew MWEs which may be exploited towards the goal of more accurate MWE identification.

In general, the behavior of MWEs can be classified by the various properties which they exhibit. These properties dictate the behavior of a MWE as a whole entity as well as the behavior of its individual constituents.

Morphological properties determine how a MWE limits transformations (i.e., inflections) to each of its constituents. For example, the Hebrew MWE bit xwlim (lit. “house of sick people”), “hospital”, allows only pluralization of its first constituent word, as in bti xwlim (“hospitals”). Its second con-
stituent is already pluralized and may not be changed. By deviating from these restrictions, the sequence of words will not retain the original meaning of the MWE. As such, the word sequence *bit xwlh* has a completely different meaning than *bit xwlim* and is always used in its literal sense (“a sick person’s house”). The same MWE also restricts any possessive inflections. While other noun-noun constructs may indeed have a possessive suffix morpheme attached to the second constituent, *bit xwlim* does not. This claim is reinforced by a Google search showing that there are 1,770,000 results for “*bit xwlim*” and none for “*bit xwlik*” with the possessive suffix. Searching for “*bit xwlh*” yielded 2,040 results but we could not find any which were intended to convey the same meaning as *bit xwlim*.

The syntactic properties of a MWE relate to its part-of-speech category. In addition, they also determine the rigidity of the constituent order. Were the lexemes in the Hebrew MWE *mša wmtn* to be swapped to *mtn wmsa*, the construct would no longer have the same original meaning. In contrast, some MWEs exhibit flexible order. The Hebrew MWE ’md ’l d’tw (lit. “(he) stood on opinion-his”), “(he) stuck to his opinion”, allows interchanging its verb and prepositional phrase due to the flexibility of Hebrew syntax. Thus, the expression ’l d’tw ’md (lit. “on opinion-his (he) stood”), carries identical semantic meaning.

The properties of a specific MWE are mandatory for a speaker to abide by in order to avoid corrupting its intended semantic meaning or rendering its context incomprehensible. We examine the diverse behavior of MWEs by presenting a heterogenous set of representative examples in Hebrew.

As in example MWE (1), MWEs may exhibit morphological fixedness; only a single inflection is permitted for each constituent. In contrast, a MWE may allow inflection for some (2) or all (3) of its constituents.

(1) \( \text{ala am kn} \)
   \begin{align*}
   \text{but if yes} \\
   \text{“unless”}
   \end{align*}

(2) \( \text{bit mšpT bti mšpT} \)
   \begin{align*}
   \text{house law , houses law} \\
   \text{“court” “courts”}
   \end{align*}
Some Hebrew MWEs can agglutinate morphemes to some or to all of their constituents. These morphemes are necessary to the semantic meaning of the MWE. These morphemes may be attached, for example, as prefixes such as prepositions amongst others (4) or suffixes such as those signifying possession (5).

(4) ‘md ’l d’tw
stood on opinion-his
“he stuck to his opinion”

(5) bgwrw aclk
in close at yours
“your fortune is nigh”

MWEs can be classified by their part-of-speech categories, such as the following constructs:

(6) **Noun-Noun** bit xwlim
house sick people
“hospital”

(7) **Verb-Preposition** ‘lh ’l
ascended on
“figure out”

(8) **Noun-Adjective** šwq šxwr
market black
“black market”

(9) **Adjective-Noun** iph npš
beautiful soul
“gentle soul”

(10) **Participle-Noun** iwsb raš
sitting head
“chairman”
(11) Conjunction  \textit{ap \ 'l \ pi}  \\
    even on times  \\
    “although”  \\

(12) Verb-Noun  \textit{p\textasciitilde{s}T \ rgl}  \\
    stretched foot  \\
    “go bankrupt”  \\

We also consider verbal phrases as valid Hebrew MWEs, those constructs composed of a verb followed by its complement. Depending on the preposition, a Hebrew prepositional complement may exist as a stand-alone word (either with inflection for object pronoun or without) or as a prefixed morpheme attached to the object to which it refers. As is the case for (13), the prepositional morpheme is necessary in order to connect the verb \textit{h\textasciitilde{t}m\textasciitilde{s}} to its object. Examples (14) and (15) show that using a different preposition with the same verb base may form a new verbal phrase with entirely different meaning. Such Hebrew verbal phrases are akin to verbal phrases in English (e.g., “look up”, “look after”).

(13) \textit{h\textasciitilde{t}m\textasciitilde{s} \ b}  \\
    used on  \\
    “use”  \\

(14) \textit{qina \ b}  \\
    envy on  \\
    “envy”  \\

(15) \textit{qina \ l}  \\
    protect (zealously) to  \\
    “protect (zealously)”  \\

1.4 Research goals

The primary goal of this thesis is to automatically construct a dictionary of Hebrew MWEs. We are able to extract candidate MWEs from other languages as well using our method, however we chose to focus on Hebrew. In doing so, we would like to investigate how morphology plays a role in
identifying MWEs and create a method which exploits the lexical and morphological structures of different languages as a basis from which to improve the identification process. In addition, we aim to explore how additional languages can be used to further improve MWE extraction.

1.5 Research methods

In this work we formulate an algorithm for identifying Hebrew MWEs from multilingual corpora. This entire process is fully automated. The algorithm relies on sets of pre-defined language-specific word transformations to generate a metamorphosed version of the original text. These transformations are essentially an implementation of a concept we term Text Isolation. We argue that data sparsity harms MWE identification accuracy. Therefore, we reduce words to canonical forms by applying these transformations in an effort to reduce data sparsity. MWE recognition is accomplished using a method for automatic word alignment based on cross-lingual co-occurrence frequency statistics. The product of our method is a dictionary of MWEs along with their translations. We demonstrate our method on multilingual corpora which we construct by aligning translated versions of movie subtitle files with each other.

1.6 Outline

This thesis is structured in the following manner. Chapter 2 discusses related work. In Chapter 3, we present our methodology in detail and elaborate on the many steps involved in producing the outcome. The results of our experiments are evaluated in Chapter 4 in which we remark on the utilities of our algorithm. Finally in Chapter 5, we discuss conclusions and offer suggestions for improvements to our research.
Chapter 2

Related Work

2.1 Automatic acquisition of MWEs

The NLP community has witnessed a growing surge in interest in MWEs over the past few years. Some of the earliest works in automatic MWE identification focused on their collocational behavior (Church and Hanks [9]). Collocation extraction has been the hot topic of many previous works and the subject of much research. The underlying idea of this approach is to compute the probability of the occurrence of a word pair in relation to the probabilities of the individual words occurring independently. Pecina [32] ranks Adj-N and PP-Verb collocation candidates by comparing various association measures including t-score, pointwise mutual information (PMI), log likelihood, and CHI$^2$. This work illustrates that there is a significant improvement over using a single collocation measure by combining different collocation measures using standard statistical methods. In an attempt to seek out a single universal measure, Villavicencio et al. [41] found that both the PMI and permutation entropy (PE) measures serve to differentiate most successfully between MWEs and non-MWEs. An extensive survey of statistical word association measures can be found in Evert [12].

Arguing that purely statistical methods using co-occurrence measures fail to identify many low frequency MWEs, Piao et al. [33] proposed that linguistic properties be taken into consideration as well. They argue that MWEs, as lexical units, carry single semantic concepts and can therefore be identified as “word bundles” representing semantic units. They use a tool which identifies MWEs from a lexicon in which each MWE has a template
which describes a pattern of words and part-of-speech tags. Some MWEs are described by possible semantic tags from a pre-defined tagset. These semantic tags are essentially categories which comprise a hierarchical structure of 21 major semantic fields (e.g., sports, psychological actions, names, science, food, etc.). They assign a set of potential semantic tags to lexical units and then choose the most contextually appropriate tag for each MWE instance. Candidate MWEs which possessed a single semantic unit were then collected and evaluated.

Purely syntactic methods attempt to extract relevant terms by analyzing specific syntactical structures. These methods utilize parsers, lexicons and language filters to aid in extracting MWEs according to their syntactic properties. Baldwin and Villavicencio [3] use a rule-based method to extract MWEs in the form of a verb and preposition using a part-of-speech tagger and a chunker which identifies verb-preposition occurrences in the corpus. These methodologies generally require sophisticated language specific techniques to isolate MWE candidates and therefore are not the most suitable choice for cross-lingual applications.

Hybrid approaches have also garnered interest, combining concepts from both statistical and linguistic methods. These methods focus on identifying non-compositional MWEs by means of analyzing both semantic and syntactic properties.

Methods which assess the syntactic behavior of candidate expressions rely heavily on part-of-speech taggers and morphological analyzers. Faizly and Stevenson [13] devise techniques to distinguish idiomatic verb-noun combinations from literal ones. Their approach combines the overall fixedness that MWEs exhibit, accounting for lexical variability in addition to syntactic flexibility (in terms of verb passivization, determiner variation, pluralization). Bannard [4] also experiments with similar syntactic variations to identify verb phrases as MWEs. Using these variation measures, they conclude that a MWE can be identified by determining that its syntactic flexibility as a whole is less than that of its parts.

A number of approaches exist which utilize semantic properties for identifying idiomatic expressions. Lin [24] presents a method based on the assumption that mutual information (MI) values differ significantly between actual idiomatic expressions and those expressions similar to their literal meaning. These values are computed by substituting a component in a can-
didate expression by a semantically related word. Van de Cruys and Villada Moirón [39] apply the same concept, replacing nouns in noun-verb combinations with pre-selected nouns and measuring compositionality by observing if the verb prefers the original noun or the substituted noun. Baldwin et al. [3] and Katz and Giesbrecht [20] utilized Latent Semantic Analysis (LSA) to measure the similarity between an MWE and its components. Here, a construction is likely to be an idiomatic MWE if the LSA measure of co-occurrence between the MWE and its literal meaning is higher than the sum of its constituent words.

Al-Haj and Wintner [1] [2] pick apart the morphological and syntactic idiosyncrasies exhibited by Hebrew noun-noun compounds (NNCs). They leverage the specific properties of this particular construction by optimizing scores for a pre-defined set of linguistically-motivated features. Each feature is essentially a count which reflects the likelihood of an NNC exhibiting one of the syntactic or morphological properties that it represents. In addition, they define features which represent collocation measures such as those mentioned earlier. They demonstrate the ability to distinguish Hebrew NNCs from non-idiomatic noun-noun constructions with high accuracy.

2.2 Exploiting multilingual parallel corpora

The aforementioned works are all based on monolingual textual resources for identifying MWEs. Multilingual parallel corpora prove to be remarkable resources for observing the transitional behavior of MWE idiomaticity into another language. Stemming from the fact that a non-compositional expression may not be translated literally nor into some combination of the literal meanings of its constituent words, MWEs can be identified along with their translations in a target language. MWE candidates and their translations may be extracted using methods of automatic word alignment on parallel corpora (Och and Ney [29]).

In one of the earlier works on the subject, Melamed [26] uses a parallel English-French corpus to identify non-compositional compounds by constructing a statistical translation model for both languages and maximizing the information-theoretic predictive value of the model.

Villada Moirón and Tiedemann [40] focus on Dutch expressions and their translations into English, Spanish and German. After performing auto-
matic word alignment on the corpus using GIZA++ (Och and Ney [29])
and collecting candidate MWEs, two measurements are performed: the
translational entropy measure reflects the diversity of translations (a non-
compositional MWE will exhibit higher diversity), and the proportion of
default alignments reflects the amount of trivial translations of the expres-
sion’s component words among the retrieved translations.

Using the Europarl corpus ([21]) as a resource, Weller and Fritzinger
[42] propose a hybrid method for identifying German MWEs in which both
monolingual and multilingual features of the candidate expressions are com-
puted. They state that idiomatic MWEs tend to be morpho-syntactically
fixed in regards to such features as number, determiner, or negation. A score
is computed for each candidate MWE, representing its behavior in terms of
these three measures. In addition, both the translational entropy and de-
fault alignment proportion measures from Villada Moirón and Tiedemann
[40] are used to indicate semantic associativity based on word equivalences.
These measures reflect the translational behavior of the MWEs in a cross-
lingual environment. They argue that the combination of these two features
of MWEs are better suited for identification of idioms than frequency.

Lee et al. [23] experiment with a Korean-English corpus, proposing a
method to perform phrase alignments rather than word alignments. They
argue that it is just as important to examine the relation between how
the individual words in a phrase are translated to how the phrase as a
whole is translated. Two scoring functions are proposed which account for
translational entropy and the variation of the translations of the candidate
phrase’s constituents; a phrase with larger translational difference than its
constituents is rewarded more.

Caseli et al. [8] use GIZA++ to word-align an English-Portuguese corpus
before extracting multi-word alignments from the results. These candidate
MWEs are disqualified if they appear less than a certain frequency thresh-
old or match certain syntactic patterns. These filtering patterns are defined
to be language specific. Even after applying several filtering patterns and
frequency treshold to their candidate MWEs, they reported a precision of
only 38% for bigrams as well as very low recall and F-measures for all ex-
periments.

Tsvetkov and Wintner [38] present a method to extract MWEs from
a small Hebrew-English corpus. They preprocessed the corpus by lemma-
tizing both languages and splitting some Hebrew morphemes into separate tokens. GIZA++ was then used to word-align the parallel sentences. They used a bilingual dictionary to verify these word alignments. Alignments which appeared in the lexicon were replaced with a dummy symbol. Those alignments which did not appear in the lexicon were left to be analyzed as participants in the compositional makeup of candidate idiomatic MWEs. Words which were not aligned by the program were also left and not replaced with the dummy symbol. Remaining word sequences served as candidate MWEs and were tested for validity using a monolingual corpus. For each multi-token sequence, they computed a score based on a variant of PMI. The sequences whose score was above a certain threshold were considered statistically significant and were extracted as valid MWEs. Similarly to this work, we perform some preprocessing steps before aligning word sequences between parallel texts in an effort to improve MWE identification.

2.3 Morphology-based word transformations

There have been some approaches to altering a text based on its morphological structure towards various goals. Many of these techniques are used as a preprocessing technique for the purpose of statistical machine translation (SMT). Motivated by the observation that many local and some nonlocal syntactic structures in English map to morphologically complex words in Turkish, Yeniterzi and Oflazer [43] presented a method of constituent re-ordering so that the English constituent order resembles that of Turkish. Their work is based on earlier works on translation from English to Turkish [El-Kahlout and Oflazer [10], Oflazer [30], Oflazer and El-Kahlout [31]]. They bridge the morphological disparity between English and Turkish by first “enriching” the morphology of English by concatenating function words along with their syntactic tags to their relationally-dependent words, and then aligning these artificial tokens to related Turkish words.

Some of this particular MT research focuses on decomposing or segmenting words of the source language before translation into the target. Goldwater and McClosky [15] preprocess the morphologically-rich Czech input in order to improve Czech-English translation. They combine various methods of word modification including simple lemmatization, morpheme decomposition, and inserting pseudowords which correspond to English function words.
which don’t exist as separate words in Czech. Nießen and Ney [27] [28] investigate various types of morphology-based restructuring techniques to harmonize word order between German-English sentence alignments. They employ many language-specific preprocessing techniques to the German text such as prepending detachable prefixes to their associated verbs, annotating frequent German MWEs with POS tags, and combining idiomatic MWEs into single words. In addition, German words are transformed into hierarchical representations using the base form of the surface word and a mixture of morphological and syntactic tags.

2.4 Movie subtitles as a resource

Movie subtitles have been acknowledged as having clear and distinct advantages for purpose of natural language processing. Methods for the construction of multilingual parallel corpora from movie subtitles have been investigated. Tiedemann [36] proposed a subtitle alignment method which relies on timing information encoded in the subtitle files. The maximal time overlap calculated between subtitles in the source and target languages is used as a clear indicator that subtitles are optimal candidates for alignment. In order to overcome timing encoding problems, frame rate discrepancies and time shifts, the semi-automatic method requires some human intervention. Itamar and Itai [18] propose a completely automatic method to handle these issues and thus, subtitles in any language are supported. A significant reduction in alignment error rate is reported. They also propose a word-alignment method which shows slight improvements in precision and recall over GIZA++ (Itamar [17]).

Lavecchia et al. [22] generate a bilingual dictionary using English and French movie subtitles as a tool for training a machine translation system. In conjunction with a translation table automatically constructed from their corpus, they produce a bilingual dictionary from the best correlated words called triggers, which are determined using Mutual Information between the translated subtitles. Using optimal parameters, their method slightly outperforms GIZA++ ([29]).

Pilevar and Feili [34] also construct a statistical machine translation system trained on a corpus composed of English and Persian movie subtitles. Understandably, their system proves to be biased towards the scripted
speech characteristic of movie subtitles, showing twice the success over translating data taken from a grammar textbook. Due to the rich morphology and numerous inflectional forms of the Persian language, their system fails to translate most multi-word compound verbs. They attribute this phenomenon partly to the deficiency of their Persian tokenization system, which was used for preprocessing the corpus.
Chapter 3

MWE Extraction

3.1 Overview

Our methodology for automatically constructing a dictionary of Hebrew MWEs and their translations consists of the following steps. We first construct a parallel English-Hebrew corpus of movie subtitle translations (Section 3.2) from subtitle files. Spanish subtitle files were also acquired to generate the parallel English-Spanish and Spanish-Hebrew corpora. We then apply Text Isolation transformations on each of the aforementioned parallel bilingual corpora, resulting in three new “isolated” corpora (Section 3.3). We discuss the tools we used to analyze raw text in each language (Section 3.4). A token-level alignment algorithm is performed on the corpora to align word sequences between subtitle translation pairs (Section 3.5). Finally, from the output of the alignment tool, we harvest candidate Hebrew MWEs in addition to harvesting their alignments from both the English and Spanish translations (Section 3.6).

3.2 Corpus construction

A collection of subtitle files was obtained for 1,055 movies\(^1\). The movies varied over many genres and debuted over a wide range of years. Each movie had three corresponding files containing subtitles in English, Spanish, and Spanish.

\(^1\)Source:http://www.opensubtitles.org. Thanks to Branislav Grezo, the administrator of the site, for his support.
Hebrew individually. We can think of the set of subtitles in each language as a monolingual corpus. We denote these monolingual corpora by $C_E$, $C_H$ and $C_S$ for English, Hebrew and Spanish respectively.

We note from the statistics shown in Table 3.1 for our monolingual corpora that $C_H$ contains far fewer tokens and individual Hebrew subtitles contain less tokens than their English and Spanish counterparts. From these observations, we gather that the same amount of information can be expressed with less tokens in Hebrew than these two other languages. This phenomenon is especially apparent for English where the ratio of English to Hebrew tokens is 1.28:1 and the ratio of characters is 1.29:1. The approximately 30% difference in token and character quantity between English and Hebrew can be foremost attributed to the morphological behavior and inflectional patterns characteristic of written Hebrew. Hebrew words contain bound morphemes which can only be expressed as free morphemes in English. In addition, Hebrew words are shorter than in English due to the lack of vowel characters (vowels are implied). This is an extremely interesting and relevant base for our discussion in Section 3.3. In the next step, we are tasked with parallelizing the three monolingual corpora.

<table>
<thead>
<tr>
<th></th>
<th>$C_E$</th>
<th>$C_H$</th>
<th>$C_S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total subtitles</td>
<td>1,166,152</td>
<td>1,143,338</td>
<td>1,150,184</td>
</tr>
<tr>
<td>Total tokens</td>
<td>7,973,074</td>
<td>6,206,868</td>
<td>6,991,886</td>
</tr>
<tr>
<td>Total unique tokens</td>
<td>272,826</td>
<td>485,905</td>
<td>353,781</td>
</tr>
<tr>
<td>Average tokens per subtitle</td>
<td>6.84</td>
<td>5.43</td>
<td>6.08</td>
</tr>
</tbody>
</table>

Table 3.1: Statistics for the English ($C_E$), Hebrew ($C_H$) and Spanish ($C_S$) monolingual corpora

Subtitle files contain subtitles which are diverse in their nature with respect to sentence delimiters. They may contain one or more sentences, a part of a sentence only, or a sentence and a part of a second sentence. In addition, subtitles are transcribed from speech and are therefore likely to contain speech disfluencies such as false starts, repeated words or syllables, fillers (grunts and utterances), and speaker repairs. These irregularities which characterize subtitles present a difficult task for sentence tokenizers and consequently sentence alignment algorithms.

We selected a sentence alignment method (Itamar and Itai [18]) which
is designed for aligning subtitles from subtitle files. The method utilizes the timing information encoded in every standard format subtitle file. By exploiting this feature, this tool determines what subtitles have overlapping time frames (appear on the screen at the same time) and are therefore likely correlated. This alignment tool can conceivably generate $1:n$ or $n:m$ subtitle alignments. Additionally, $0:n$ alignments may be created due to the variation in subtitle file authorship (e.g. opening credits for a film intended for an English-speaking audience appear in the Hebrew translation, but will understandably not appear in the English subtitle file).

For each movie in the collection, and for each language pair, the respective subtitles were aligned using the subtitle alignment method. This resulted in three parallel bilingual corpora containing aligned subtitle translations. These parallel bilingual corpora are denoted by $C_{E,H}$ (English-Hebrew), $C_{E,S}$ (English-Spanish) and $C_{S,H}$ (Spanish-Hebrew). Table 3.2 shows subtitle alignment statistics for these parallel corpora.

In the next step, we filtered out any bad or useless subtitle alignments from the parallel corpora. First, any $0:n$ alignments were discarded. Additionally, any bilingual alignments which did not correlate across all three language pairs were discarded from the corpora.

<table>
<thead>
<tr>
<th>Alignment</th>
<th>$C_{E,H}$</th>
<th>$C_{E,S}$</th>
<th>$C_{S,H}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0:1</td>
<td>20,836</td>
<td>17,953</td>
<td>26,214</td>
</tr>
<tr>
<td>1:0</td>
<td>33,552</td>
<td>28,134</td>
<td>27,244</td>
</tr>
<tr>
<td>1:1</td>
<td>1,002,607</td>
<td>986,938</td>
<td>954,277</td>
</tr>
<tr>
<td>1:2</td>
<td>36,599</td>
<td>46,068</td>
<td>52,777</td>
</tr>
<tr>
<td>2:1</td>
<td>46,697</td>
<td>52,506</td>
<td>57,943</td>
</tr>
<tr>
<td>Total</td>
<td>1,140,291</td>
<td>1,131,599</td>
<td>1,118,455</td>
</tr>
</tbody>
</table>

Table 3.2: Statistics of the subtitle alignment algorithm on the parallel corpora

### 3.3 Text Isolation

One of the major shortcomings of token-based alignment methods is that they are prone to data sparsity. As such, words which appear at low frequency in the corpus tend to be incorrectly aligned because there is not
enough data to reinforce weak co-occurrence relationships. Morphological richness compounds the data sparsity problem. In a morphologically rich language, a word may encode a number of, and sometimes unboundedly many (e.g., Finnish), morphemes in addition to its lemma. Naturally, this results in the possibility of many unique word forms. Hebrew is a morphologically rich language whose words inflect to encode complex information. For instance, the lemma zkwt (lit. “right”) may appear unmarked as a stand-alone word. However, it may also appear in an inflected surface word form carrying additional information such as in wk˘ slzkwiwtihm (lit. “and-when-for-rights-their”), “and when for their rights”. In English, on the other hand, most of the concatenated Hebrew morphemes may only be expressed as separate orthographic words. These differences in language features exacerbate the data sparsity issue when word-aligning morphologically rich languages and therefore necessitate a solution.

We aim to mitigate the effects of data sparsity in our corpus by attacking the issue of morphological complexity. We present a concept of applying language-specific lexical, morphological and orthographic transformations to a parallel bilingual corpus in an effort to improve word alignment and thus MWE identification.

We define Text Isolation as the reconstruction of a source sentence in which certain lexemes and morphemes, the morphological components of each word, are decomposed and segmented into stand-alone “words”. These morphemes represent the basic building blocks of words. During the segmentation process, each morpheme is split from its source word and undergoes some pre-defined transformation. We defined transformations (Appendix A) which often normalize a source word and strip it of some of its morphological features. In other words, we intentionally disregard certain morphemes in the transformation’s output. In essence, an isolated sentence is assembled from the basic word constructs of the source. The order of transformed morpheme tokens is preserved in the isolated sentence. Figure 3.1 shows an example in which an English sentence is first tokenized, and a transformation has been applied on each word (and morpheme) to convert it to its lemma (root word). We discuss morpheme transformations further in this section.

Our ultimate goal in performing Text Isolation is to adapt as much as possible the structure of languages to a standard structure, a common
a. He took a nap after he finished playing with his toys
b. He take a nap after he finish play with his toy

Figure 3.1: Text Isolation on example English sentence; (a) original sentence, (b) isolated sentence

standard. This entails normalizing the structure of morphologically diverse languages. By doing so, we will show that the isolation process will serve as a vehicle for more accurate word alignment. This lies behind our motivation for Text Isolation. Our common standard of choice for this task is a isolated form of text in which morphological and lexical components of the source text have been segmented into separate tokens. Even for English, which is already a relatively isolated language, we perform some level of transformation using Text Isolation. We define custom word and morpheme transformations which separate internal word structures such that morphologically richer languages will resemble this common standard.

We carry out Text Isolation in three main phases. As an initial step, we tokenize each raw input sentence. Tokenization involves breaking up text into meaningful character sequences called tokens. These tokens will then be used for input for our morphological analysis tools. A tokenizer may be language specific. For example, an English tokenizer will separate contractions into two individual tokens.

After tokenization, a morphological analyzer is used to retrieve a set of surface word analyses, each describing a possible configuration of each surface word’s morpheme composition. Morphological analysis plays a key role in the Text Isolation process. A morphological analyzer is necessary for stripping a surface word of its inflections and deciphering the syntactic information carried by these inflections. In the example sentence  They are meeting, the analyzer will report multiple morphological analyses for the surface word  meeting. One analysis will describe the word as a singular gerund noun, while a different analysis will describe it as the present participle form of the verb  meet. Due to the fact that one or more morphological analyses may be derived from the same surface word, a morphological disambiguation tool can be used to determine the most suitable analysis. In the example
sentence above, a disambiguation tool will likely give a higher probability score to the verb analysis than the noun analysis. Disambiguation tools may determine the most suitable analysis in various ways, including using information determined from the local context in which the word appears and by calculating statistical likelihood based on training corpora. For English, we used a part-of-speech tagger which was sufficient for morphological disambiguation (Section 3.4). A part-of-speech tagger is critical for reducing syntactic ambiguity. For each surface word, the most suitable analysis is chosen from the set of morphological analyses. This analysis will be used to decompose the surface word. The analysis will dictate the custom transformations that are to be performed on the morphemes and the order in which the individual morphemes should be segmented.

Defining word and morpheme transformation functions is an integral part of Text Isolation. Since all transformations are language-specific, this requires a deep understanding of the morphology of the language. A transformation function accepts as input a morphological analysis describing the morpheme composition of a word. Given the most likely morphological analysis, the function outputs a segmented representation of selected morphemes for the surface word that were outlined in the analysis. Each morpheme may further undergo a morpheme-specific transformation process. In some cases, especially for Hebrew, certain lexical elements underwent transformations to their identical source form. In other words, they were left untouched.

Unlike English, Spanish allows object pronouns to be suffixed to a verb. In order to adapt raw Spanish text to the structure of the common standard, we define transformations which split such words into multiple isolated tokens. For example, the Spanish word *dámelo* (lit. “give me it”), which has the morpheme composition *dá+me+lo*, is isolated to *dar me lo*. The inflected verb *dá* is converted to its base infinitive *dar* and each attached preposition has been isolated and transformed to the stand-alone version of itself. Figure 3.2 illustrates examples of Text Isolation for all three of our experimental languages.

Not all constituent morphemes of a surface word may have transformations defined for them. For instance, we chose not to define a transformation for morphemes representing plurality. For the English plural noun *animals* (*animal+s*), the final isolated output would be *animal*. Essentially, this describes the process of lemmatization transformations we performed on words
a.) many hours passed after the water was drawn
many hour pass after the water be draw

b.) ayúdame a encontrarle
ayudar me a encontrar le

c.) bt dwdtì nšrh mhawnibrșîTh
bt dwdh šli nšr m h awnibrșîTh

Figure 3.2: Text Isolation examples: (a) English, (b) Spanish, and (c) Hebrew

and is fueled by our motivation towards our common standard structure.

We are aware that these surface word transformations come at a cost. There may be some level of information which is lost as a result of these transformations. For example, we transform passive English verbs to their lemma form. The surface word eaten is transformed to eat, losing the information from the morpheme -en possibly indicating passive voice. Although we can distinguish between the active and passive voice in English, we chose to ignore the passive role by simply transforming such verbs into their lemmas. Our motivation for this decision stems from the fact that in English, both active and passive voices may be represented by identical surface forms of the same verb. This is demonstrated in such sentences as I have eaten lunch and My lunch is eaten where the surface word eaten exhibits active voice in the former case and passive voice in the latter. The transformation of the English verb into its lemma always results in the active form of the verb. In contrast, in Hebrew the passive form of a verb is an entirely separate phonological verb template, termed binyan (plural, binyanim), and possesses its own inflectional behavior. Therefore, the passive naklw (lit. “they were eaten”) is transformed into the lemma nakl (binyan np’l) whereas the active aklw (lit. “they ate”) is transformed into the lemma akl (binyan p’l). Each passive binyan has an active binyan counterpart. This begs the question of why we did not transform the passive Hebrew verbs to their active forms by simply reversing the binyan. There are two reasons for which we opted not to. First, there are exceptions in regards to verbs of the passive binyan np’l; verbs in this binyan are passive in most cases, but not all. The verb
lhikns (lit. “to enter”), for example, is not a passive verb yet exists in the binyan np’l and is inflected as such. Furthermore, this verb does not have a counterpart in the active counterpart binyan p’l. Secondly, we opted not to reverse the binyanim of the passive Hebrew verbs for empirical reasons. We conducted an experiment in which we reversed a small sample set of verbs of the passive binyan pw’l in our corpus to their counterparts of the active binyan pi’l and then word-aligned the corpus. Yet, we did not observe any improvement in the alignment accuracy.

Text Isolation was performed on the parallel corpus described in Section 3.2. According to this process, pre-defined language-specific transformations were applied to each respective subtitle of each alignment pairing. This resulted in new isolated parallel corpora containing only aligned isolated subtitles. Appendix A contains a list of transformations used for each of our experimental languages.

Table 3.3 shows some statistics for the tokens and words which compose the set of subtitles in each language for the three original parallel corpora $C_{E,H}$, $C_{S,H}$ and $C_{E,S}$. We note the large difference in unique tokens between English and the other two languages. This is a clear sign of data sparsity in the corpora. This phenomenon can mainly be attributed to the larger number of inflectional forms in Hebrew and Spanish than in English. Table 3.4 shows similar statistics for the three isolated parallel corpora $C_{I,E,H}$, $C_{I,S,H}$ and $C_{I,E,S}$. In this table, we observe the resulting balance in the number of unique word forms between the three languages, reducing the data sparsity in the isolated corpora. In the next step, we will discuss how this apparent reduction in the data sparsity in the corpora encourages stronger cross-lingual correlation statistics to be computed for word sequences.

<table>
<thead>
<tr>
<th></th>
<th>English</th>
<th>Hebrew</th>
<th>Spanish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total # of tokens</td>
<td>7,507,198</td>
<td>5,889,749</td>
<td>6,643,272</td>
</tr>
<tr>
<td>Total # of unique tokens</td>
<td>78,706</td>
<td>167,326</td>
<td>115,944</td>
</tr>
</tbody>
</table>

Table 3.3: Statistics for the tokens which compose the original parallel corpora $C_{E,H}$, $C_{S,H}$ and $C_{E,S}$. 
Table 3.4: Statistics for the tokens which compose the isolated parallel corpora $C_{E,H}^I$, $C_{S,H}^I$ and $C_{E,S}^I$

<table>
<thead>
<tr>
<th></th>
<th>English</th>
<th>Hebrew</th>
<th>Spanish</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total # of tokens</td>
<td>7,498,172</td>
<td>6,816,123</td>
<td>6,760,470</td>
</tr>
<tr>
<td>Total # of unique tokens</td>
<td>66,403</td>
<td>61,582</td>
<td>81,011</td>
</tr>
</tbody>
</table>

3.4 Language analysis tools

Our methodology requires a parallel bilingual corpus. We use the corpus which we described in Section 3.2. In order to isolate raw text, we assume the following tools are available: tokenizer, part-of-speech tagger or both a morphological analyzer and disambiguator. Freely available tools were selected for each of our experimental languages: English, Spanish, and Hebrew.

Numerous tools exist for analyzing English text. We chose to use a toolkit provided by the Stanford NLP Group (Toutanova et al. [37]), which includes a tokenizer and POS tagger. For Spanish, we used Freeling (Carreras et al. [7]), an open source language analysis tool suite.

The APIs for English and Spanish allow the user to input raw text and immediately retrieve the POS and the most likely morphological analysis for each word in the input. In contrast to processing English and Spanish, processing Hebrew text entailed executing the morphological analyzer and disambiguation tools separately, then selecting the most likely analysis (with the highest score). Morphological analysis for Hebrew text was performed using the MILA Morphological Analysis Tool (Itai and Wintner [16]). The morphologically-analyzed text outputted by this tool was then fed as input to MorphTagger (Bar-Haim et al. [6]), the MILA Morphological Disambiguation Tool, which assigns scores for each morphological analysis. Both the analysis and disambiguation tools are provided by the Knowledge Center for Processing Hebrew (MILA). We chose to use these tools because they were freely available, displayed acceptable performance, and provided us with all the information which we required.

We wrote a thorough API to streamline our entire method. This API allowed us to easily perform all the steps necessary to generate the parallelized subtitle input files, pipeline the morphological processing of texts for
any language, phrase-align the corpora, and extract and record statistics for
word alignments.

3.5 Identifying MWE candidates

As mentioned, the motivation behind our approach to MWE identification is
that many misalignments are caused by data sparsity, characteristic of mul-
tilingual parallel texts. Morphological diversity between languages amounts
to weak co-occurrence measures in statistical word alignment algorithms.
We therefore propose a method to overcome this phenomenon, thus reduc-
ing the effects of morphological diversity on misalignment and extracting
MWEs more accurately.

We perform Text Isolation on the bilingual parallel corpora as discussed
in Section 3.3 using pre-defined language-specific morpheme transforma-
tions. We selected a word-level alignment method for aligning word se-
cquences between two languages which uses statistical translation models
(Itamar [17]). A model was trained on movie subtitles for each of our ex-
perimental languages. This method was chosen over the commonly-used
GIZA++ tool (Och and Ney [29]) because of the superiority in word align-
ment results shown over those of GIZA++. Once trained, the method works
by calculating probabilities of correlated “translation units”, a group of one
or more tokens in each pair of aligned subtitles. The most optimal word
alignment configuration is computed for each subtitle alignment. The tool
outputs word sequence alignments between each pair of translated subtitles.
Each aligned word sequence contains one or more tokens. An example of
token-level alignment between two subtitles is demonstrated in Figure 3.3.
The figure also illustrates how Text Isolation can improve identification of
MWEs and improve alignment in general by reducing misalignments which
may have occurred in the original corpus.

For each language pair, aligned subtitle pairs were word-aligned using
this tool. We then harvested potential MWEs from the alignment tool’s
output by extracting only those alignments which contained more than one
Hebrew token. These multi-token Hebrew word sequence alignments are in-
teresting because their constituent words are strongly correlated. We expect
that such aligned multi-token word sequences will exhibit non-compositional
behavior characteristic of MWEs.
1.) on Sunday₁ when there₂ is a lesson₃ in our school  
   biwm₁ rašwn₁ kšbbit sprinw ihih₂ ši‘wr₃

2.) on Sunday₂ when₃ there₄ is a lesson₅ in₆ our₇ school₈  
   b₁ iwm₂ rašwn₂ kš₃ b₆ bit₈ spr₈ šlnw₇ ihḥ₄ ši‘wr₅

Figure 3.3: Token-level alignment example. Tokens with identical subscripts are co-aligned.

3.6 Harvesting MWE alignments

In the process of identifying candidate Hebrew MWEs, a byproduct of the word sequence alignment tool discussed in Section 3.5 is a set of alignments from the translated (English and Spanish) subtitles, corresponding to each identified multi-token Hebrew word sequence. Understandably, separate appearances of a single word sequence throughout the corpus may be aligned. In such cases where the same sequence has appeared and been aligned in multiple translation pairs, the translation to which the sequence has been aligned may not be identical in all instances. As Figure 3.4 illustrates, for example, the alignment tool aligned the Hebrew token sequence bit spr to the English tokens “school”, “university”, “principal” and “student” in different instances. From all such subtitle translation pairs in which such multi-token sequences appear and have been aligned, we collect all corresponding alignments from the translations. Each harvested set of alignments serves as a dictionary of possible translations for each candidate MWE. We also record the number of times (frequency) each alignment to the candidate MWE was made by the alignment tool (Table 3.5). The relatively high frequency at which a word sequence is aligned to a candidate MWE serves as an indicator that the sequence is a correct translation.
1. he₁ be the₂ director₃ of the school₄ of hogwarts₅  
   hwa₁ h₂ mnhl₅ bit₄ spr₄ hgwwr₅  
2. but i₁ think₂ that₃ you should₄ return₅ to₆ the₇ university₈  
   ani₁ xšb₂ š₃ hwTb₄ š xzr₅ l₆ h₇ bit₈ spr₈  
3. marina₁ of₂ pretensa₃, student₄ mage₅  
   mrinh₁ m₂ prTnzḥ₃ h ṭlmd bit₄ spr₄ l qsm₅  
4. it₁ be bigger₂ than₃ the₄ principal₅ office₆  
   zh₁ iwtr₂ gdwl₂ m₃ h₄ mšrd₆ šl h mnhl bit₅ spr₅  

Figure 3.4: Examples of alignments for the Hebrew multi-token sequence  
*bit spr*

<table>
<thead>
<tr>
<th>Alignment</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>school</td>
<td>886</td>
</tr>
<tr>
<td>university</td>
<td>53</td>
</tr>
<tr>
<td>student</td>
<td>3</td>
</tr>
<tr>
<td>principal</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>945</td>
</tr>
</tbody>
</table>

Table 3.5: Alignment frequency (number of occurrences) for the Hebrew token sequence *bit spr*
Chapter 4

Results and Evaluation

Our evaluation goal is to assess our method’s ability to identify Hebrew MWEs in the original corpus versus that of our isolated corpus. Following word-level alignment between each pair in our trilingual parallel corpus, we retained only those Hebrew alignments containing two or more tokens. We extracted these Hebrew multi-token sequences from the word-level alignments of the subtitle pairs in $C_{E,H}^I$ and later from $C_{S,H}^I$.

4.1 MWE identification

We will first examine our performance on the English-Hebrew texts. We define $SEQ_{E,H}$ and $SEQ_{E,H}^I$, the sets of Hebrew multi-token sequences extracted from only the English-Hebrew alignments from $C_{E,H}$ and $C_{E,H}^I$ respectively. We will evaluate these two sets containing candidate MWEs and compare our performance between them.

Table 4.1 shows some statistics for sets $SEQ_{E,H}$ and $SEQ_{E,H}^I$. We note the significant difference in size between the two sets. This is attributed to the reduction in the number of unique surface word forms resulting from Text Isolation transformations. Thus, different forms of the same MWE in $SEQ_{E,H}$ that differ only in morphological properties collapse into a single form in $SEQ_{E,H}^I$. Moreover, this reduces data sparsity. There are consequently much less unique bigrams that appear in the isolated corpus. Unsurprisingly, this also caused an increase in the total number of occurrences of the extracted multi-token sequences in $SEQ_{E,H}^I$. 

30
We will discuss an additional experiment which was performed in order to evaluate the success of the word-level alignment tool in aligning the same MWEs in the isolated corpus as it was able to align in the original corpus, or improve for that matter. There are many unique sequences in $SEQ_{E,H}$ which are in fact inflections of the same expression. For example, the sequence $hkti mkwt$ (“I got into a fight”) and $hkws mkwt$ (“They got into a fight”) are inflections of a single MWE. In the isolated corpus, both of these surface word sequences would be transformed to a single form ($hk mkh$). We conducted an experiment in order to estimate the number of such unique expressions in $SEQ_{E,H}$. We performed Text Isolation on each sequence in $SEQ_{E,H}$. The number of unique isolated sequences resulting from this process amounted to 28,950. As per the information contained in Table 4.1, we witnessed a 20% reduction from the original size of $SEQ_{E,H}$. From the results of this experiment, we noticed that $SEQ_{I,E,H}$ contains roughly half as many unique sequences as $SEQ_{E,H}$.

The results of the above experiment are interesting because we would like to investigate the capability of the alignment program to recognize the same valid MWEs in the isolated corpus as it did in the original corpus. We tested such extraction consistency by examining what valid MWEs extracted in $SEQ_{E,H}$ were also extracted in $SEQ_{I,E,H}$. In the same turn, we also measured how many invalid MWEs are no longer extracted or retained in $SEQ_{I,E,H}$. From four representative (equally frequency-distributed) sample sublists, we randomly selected a sample of 50 valid MWEs and 50 invalid MWEs (sublist II was not large enough to select 50 MWEs from it). If the isolated form of a selected MWE was in $SEQ_{I,E,H}$, then that MWE was retained, otherwise lost. Table 4.2 shows the results of this experiment. We

<table>
<thead>
<tr>
<th></th>
<th>$SEQ_{E,H}$</th>
<th>$SEQ_{I,E,H}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of bigrams</td>
<td>35,151</td>
<td>13,903</td>
</tr>
<tr>
<td>Number of trigrams</td>
<td>1,116</td>
<td>696</td>
</tr>
<tr>
<td>Number of four-grams</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td>36,268</td>
<td>14,601</td>
</tr>
<tr>
<td>Number of occurrences</td>
<td>284,154</td>
<td>298,927</td>
</tr>
</tbody>
</table>

Table 4.1: Statistics for aligned Hebrew word sequences from English-Hebrew sources
consider the loss of the valid MWEs to be negligible and note the remarkably large reduction in the quantity of “garbage” (invalid MWEs).

<table>
<thead>
<tr>
<th>Sublist</th>
<th>Valid MWEs</th>
<th></th>
<th></th>
<th>Invalid MWEs</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Retained</td>
<td>Lost</td>
<td>Total</td>
<td>Retained</td>
<td>Lost</td>
<td>Total</td>
</tr>
<tr>
<td>II</td>
<td>10 (100%)</td>
<td>0 (0%)</td>
<td>10</td>
<td>14 (66.6%)</td>
<td>7 (33.3%)</td>
<td>21</td>
</tr>
<tr>
<td>IV</td>
<td>45 (90%)</td>
<td>5 (10%)</td>
<td>50</td>
<td>24 (48%)</td>
<td>26 (52%)</td>
<td>50</td>
</tr>
<tr>
<td>VI</td>
<td>44 (88%)</td>
<td>6 (12%)</td>
<td>50</td>
<td>21 (42%)</td>
<td>29 (58%)</td>
<td>50</td>
</tr>
<tr>
<td>VIII</td>
<td>36 (72%)</td>
<td>14 (28%)</td>
<td>50</td>
<td>17 (34%)</td>
<td>33 (66%)</td>
<td>50</td>
</tr>
</tbody>
</table>

Table 4.2: Results of assessing extraction consistency of valid and invalid MWEs following Text Isolation

The simplification and reduction of word forms by Text Isolation causes the alignment algorithm to calculate stronger co-occurrence measures for frequently occurring N-grams. Thus, infrequent inflectional word forms are less likely to be misaligned when transformed to their isolated form.

Conforming with standard measurement techniques in the field of information retrieval, we use precision and recall to evaluate our results. Precision is defined as the ratio of relevant instances to the total instances retrieved. For our purposes, precision is:

\[ P = \frac{|V \cap C|}{|C|} \]

where \( V \) is the set of all valid MWEs in the corpus and \( C \) is the set of candidate MWEs extracted by the alignment program. Recall is defined as the ratio of relevant instances retrieved to the total relevant instances. For our purposes, recall is:

\[ R = \frac{|V \cap C|}{|V|} \]

Ideally, we would like to analyze the success of MWE identification by calculating precision on the entire sets of aligned word sequences. This would entail manually annotating each element in the set as a valid or invalid MWE. However, since there are thousands of sequences in \( SEQ_{E,H} \) and \( SEQ_{E,H}^I \), manual validation of all candidates was not feasible. Neither does checking only the most frequently aligned sequences provide an accurate estimate of precision because we expect frequent and infrequent sequences to
exhibit different alignment behavior. Meaning, infrequent sequences suffer more from data sparsity than frequent sequences. Furthermore, it is our intention to explore how precision varies as a function of frequency range. We use the term frequency to refer to how many instances a sequence was aligned by the word-level alignment tool in the corpus. We therefore formulated the following evaluation strategy. Both \(SEQ_{E,H}\) and \(SEQ^I_{E,H}\) were ranked individually in decreasing order by their alignment frequency. Each sorted list of sequences was split into 10 sequential sublists such that the number of occurrences of the sequences within each sublist constituted approximately 10% of the total number of occurrences of the original list. The sequence distribution comparisons are presented in Table 4.3, in which the sizes of the generated sublists for \(SEQ_{E,H}\) and \(SEQ^I_{E,H}\) are shown.

<table>
<thead>
<tr>
<th>Result set</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
<th>IX</th>
<th>X</th>
</tr>
</thead>
<tbody>
<tr>
<td>(SEQ_{E,H})</td>
<td>10</td>
<td>31</td>
<td>78</td>
<td>175</td>
<td>367</td>
<td>754</td>
<td>1,657</td>
<td>3,968</td>
<td>10,051</td>
<td>19,177</td>
</tr>
<tr>
<td>(SEQ^I_{E,H})</td>
<td>2</td>
<td>7</td>
<td>18</td>
<td>32</td>
<td>62</td>
<td>123</td>
<td>242</td>
<td>554</td>
<td>1,944</td>
<td>11,617</td>
</tr>
</tbody>
</table>

Table 4.3: Sublist sizes, in number of their element sequences, for \(SEQ_{E,H}\) and \(SEQ^I_{E,H}\)

From each sublist, we selected a sample of sequences and annotated them to determine the validity of each candidate MWE. For sublists containing less than 200 sequences, we graded the entire sublist. For sublists larger than 200 sequences, we randomly selected 200 phrases from each sublist for evaluation. From our experience, we concluded that a sample of 200 sequences is a good representation of the sublist. When experimenting with smaller sample sizes, we observed large fluctuations in the results and were unable to see a clear trend, thus indicating that our sample size was too small.

Precision is calculated independently for each sublist as the percentage of valid MWEs, as determined by our annotations, in the set of candidates selected from the sublist. Figure 4.1 shows the results of this evaluation step. From the figure, we can derive a number of observations. It is clear from the figure that \(SEQ^I_{E,H}\) shows improved performance over \(SEQ_{E,H}\) in precision for most sublists. For some sublists, \(SEQ^I_{E,H}\) exhibits a precision more than twice that of \(SEQ_{E,H}\). We observed that a low population of a sublist allows
Figure 4.1: Precision comparison by sublist between original ($SEQ_{E,H}$) and isolated ($SEQ^I_{E,H}$) English-Hebrew MWEs

for extreme precision measures such as for the case of sublist I (the first sublist) in $SEQ^I_{E,H}$. The sublist has zero precision because it contains only two sequences which, albeit extremely frequent, were annotated as invalid MWEs. As we expected, for both result sets, precision generally decreases as the sequences in the sets become more infrequent. This indicates that our success in extracting a valid MWE is related to its frequency.

Calculating recall is a difficult task because we do not have a complete list of all MWEs that appear in our corpus. Instead, we obtained a pre-compiled list of 1,585 MWEs and checked them against the extracted phrases. From the list, 636 MWEs were found in the corpus. Recall was calculated for $SEQ_{E,H}$ and $SEQ^I_{E,H}$ using this list of 636 MWEs. The overall recall for $SEQ_{E,H}$ was 44.3% and 36.3% for $SEQ^I_{E,H}$. The 8% decrease in recall can be attributed to a number of factors. We perform a survey of error sources in Section 4.4.
4.2 Precision of MWE alignments

As mentioned in Section 3.6, we extracted the set of English alignments for each corresponding Hebrew sequence to which they were aligned. We also kept track of how many times each English sequence co-aligned with each Hebrew sequence. Word-level alignment precision was measured by calculating the percentage of correct alignments in the set of extracted alignments. We calculated alignment precision for those sample MWEs selected from the sublists in Section 4.1 and annotated them for their validity as MWEs.

We compared our performance in identifying correct MWE alignments between sample MWEs from $SEQ_{E,H}$ and $SEQ^{I}_{E,H}$. Figure 4.2 shows the results of measuring MWE alignment precision per sublist in both sets. We reencounter the same phenomenon of zero precision for sublist I of $SEQ^{I}_{E,H}$ because it contains no valid MWEs. Overall, the alignment precision for $SEQ_{E,H}$ is higher than for $SEQ^{I}_{E,H}$. Note that the alignment precision for infrequently occurring Hebrew MWEs in $SEQ^{I}_{E,H}$ is significantly higher than that of $SEQ_{E,H}$. We can conclude that the products of Text Isolation transformations encourage the word-level alignment tool to make more precise alignments. Also, we observed that the amount of incorrect alignments are reduced for MWEs from $SEQ^{I}_{E,H}$. Incorrect alignments, such as those observed for valid MWEs in $SEQ_{E,H}$, are a result of data sparsity in $C_{E,H}$. Text Isolation helps to resolve this issue and improve alignment quality.

4.3 Three languages are better than two

In addition to morphological structure, the grammar and word order of a language play a large role in dictating alignment quality. For example, in contrast to English in which adjectives appear before the noun, Hebrew adjectives appear after it. Although this may be overcome by an intelligent alignment program, in some cases such phenomena cause the alignment tool to permeate misalignments of tokens surrounding such instances of cross-lingual differences. We would like to investigate how exploiting additional alignments between similarly structured languages may improve performance in identifying MWEs in addition to their alignments in the translations.
We chose Spanish as our third experimental language, having similar inflectional patterns and word order as Hebrew. Although far from being identical to Hebrew in structure, we expect Spanish will contribute a different perspective into how MWE identification performance varies across different language pairs.

4.3.1 MWE identification

We would first like to exhibit improvement in the performance of identifying Hebrew MWEs from alignments between Hebrew and another language with a morphology different than that of English. From the original Spanish-Hebrew corpus, $C_{S,H}$, we generated the isolated corpus $C_{S,H}^I$. The subtitle alignments in $C_{S,H}^I$ were word sequence-aligned using the same methodology as was used on $C_{E,H}^I$. We created the set $SEQ_{S,H}^I$, the set of multi-
token Hebrew word sequences from the Spanish-Hebrew alignments resulting from this process. The same precision evaluation methodology was applied here as in Section 4.1. Sizes for those sublists generated for $SEQ_{S,H}$ and $SEQ^I_{S,H}$ are listed in Table 4.4 for reference. From Figure 4.3, we can conclude that Hebrew MWE identification can also be improved by Text Isolation using Spanish.

<table>
<thead>
<tr>
<th>Result set</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
<th>IX</th>
<th>X</th>
</tr>
</thead>
<tbody>
<tr>
<td>$SEQ_{S,H}$</td>
<td>9</td>
<td>25</td>
<td>71</td>
<td>157</td>
<td>328</td>
<td>698</td>
<td>1510</td>
<td>3623</td>
<td>9564</td>
<td>23553</td>
</tr>
<tr>
<td>$SEQ^I_{S,H}$</td>
<td>2</td>
<td>5</td>
<td>17</td>
<td>31</td>
<td>60</td>
<td>136</td>
<td>271</td>
<td>610</td>
<td>2080</td>
<td>11679</td>
</tr>
</tbody>
</table>

Table 4.4: Sublist sizes, in number of their element sequences, for $SEQ_{S,H}$ and $SEQ^I_{S,H}$

We would now like to explore how the Spanish-Hebrew alignments from $C^I_{S,H}$ can further improve our performance in identifying Hebrew MWEs. The sequences from both $SEQ^I_{E,H}$ and $SEQ^I_{S,H}$ were combined to form the set $SEQ^I_{E,H} \cup SEQ^I_{S,H}$. This union set is the set of isolated Hebrew word sequences such that each sequence is in either $SEQ^I_{E,H}$ or $SEQ^I_{S,H}$, the sets of sequences extracted from English-Hebrew and Spanish-Hebrew alignments, respectively. Again, the same precision evaluation methodology was performed for $SEQ^I_{E,H} \cup SEQ^I_{S,H}$. We compare this performance against that of $SEQ^I_{E,H}$ and $SEQ^I_{S,H}$ individually in Figure 4.4. The added performance of the union set is not realized until sublist VIII. From sublist VIII and on, the decrease in precision is less emphasized than that exhibited by both $SEQ^I_{E,H}$ and $SEQ^I_{S,H}$. The addition of Hebrew alignments from $SEQ^I_{S,H}$ enabled us to increase our precision for the more infrequently occurring sequences. We can draw a very important conclusion from this phenomenon, being that sets of alignments between a language (Hebrew) and multiple individual languages (English and Spanish) can be combined to improve performance in identifying infrequent MWEs.

4.3.2 MWE alignments

The next step in evaluating how Spanish-Hebrew alignments may improve our performance is to exploit the alignments themselves in order to refine the
dictionary of possible translations for each MWE. Our reasoning is that the list of translations can be verified for a particular MWE by intersecting the MWE’s alignment in one language with that of another language. Specifically, we can make a stronger claim about the Hebrew MWE’s English or Spanish translations (alignments) if those English and Spanish alignments translate (align) to themselves.

We perform the Text Isolation process on $C_{E,S}$, the English-Spanish parallel corpus, thus generating the isolated version $C'_{E,S}$. The subtitle pairs in $C'_{E,S}$ are then aligned using our chosen word-level alignment tool. Word sequence alignments of all lengths are then harvested from $C'_{E,S}$ providing us with $SEQ'_{E,S}$.

We took a representative sample of valid Hebrew MWEs from each sublist in $SEQ'_{E,H} \cup SEQ'_{S,H}$ as in Section 4.2. For each MWE, we performed the following steps. Both its English and Spanish alignments were taken.

Figure 4.3: Precision comparison by sublist between original ($SEQ_{S,H}$) and isolated ($SEQ'_{S,H}$) English-Hebrew MWEs
from the token-level alignments of $C_{E,H}^I$ and $C_{S,H}^I$ respectively. Then, we discarded its English alignments which were not aligned to any of its Spanish alignments in $C_{E,S}^I$. This triangular verification technique provided us with a slight improvement in the quality of the MWE translation dictionary constructed from these alignments. For the sublists in which these samples of MWEs appeared, we calculated a precision score from the results of this experiment. This score is an average of scores representing how translatable (as determined by our knowledge of both languages) the set of extracted alignments for each sample MWE. Figure 4.5 shows this precision score for the extracted English alignments of the sample.

Some Hebrew sequences have alignments between one language but not the other. The expression *bit spr* frequently aligns individually with “school” and “university” in $C_{E,H}^I$, as well as “escuela” and “universidad” in $C_{S,H}^I$. The Hebrew phrase *wrr sqrnwt* (lit. “wake curiosity”), “spark curiosity”,

\[ \text{Figure 4.4: Effects of using a third language on MWE identification precision} \]
however, was only found in $SEQ_{E,H}^I$ and not in $SEQ_{S,H}^I$ not only due to its infrequency, but also because of the diversity and quality of its Spanish translations as contrasted by the consistency of its English translations. This demonstrates that translation consistency strengthens the statistical bond between word sequence alignments and therefore affects alignment capability in general.

4.4 Error Analysis

We would like to understand the reasons why we experienced a decrease in MWE recall for our isolated corpus. Our goal is to quantify the various sources of errors which led to the misidentification of valid MWEs. We recap the general steps of our extraction algorithm as an aid to understanding the sources of such errors. First, translated subtitles are aligned per
movie. Then, the subtitles are pre-processed using our language-specific Text Isolation transformations. Aligned subtitles undergo word-alignment and multi-token word sequence alignments are extracted as MWE candidates. At each step of the algorithm, errors may occur which cause valid MWEs to be ignored. We analyzed a single instance in $C_{E,H}^I$ of each of the 405 MWEs in $SEQ_{E,H}^I$ which was not identified. This analysis led to the discovery of a number of error sources discussed below. Table 4.5 lists the error sources and the results of our error investigation.

<table>
<thead>
<tr>
<th>Error source</th>
<th>Non-recalled MWEs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subtitle translation quality</td>
<td>62</td>
</tr>
<tr>
<td>Overaggressive Text Isolation</td>
<td>9</td>
</tr>
<tr>
<td>Subtitle alignment tool</td>
<td>15</td>
</tr>
<tr>
<td>Tagger and morphological analyzer/disambiguator</td>
<td>39</td>
</tr>
<tr>
<td>Word-level alignment tool</td>
<td>280</td>
</tr>
<tr>
<td>...Individually aligned MWE constituent tokens</td>
<td>108</td>
</tr>
<tr>
<td>...Shortest most correct partial alignment</td>
<td>28</td>
</tr>
<tr>
<td>...Partial incorrect alignment</td>
<td>91</td>
</tr>
<tr>
<td>...Incorrect alignment</td>
<td>53</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>#</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>62</td>
<td>15.31</td>
</tr>
<tr>
<td>9</td>
<td>2.22</td>
</tr>
<tr>
<td>15</td>
<td>3.70</td>
</tr>
<tr>
<td>39</td>
<td>9.63</td>
</tr>
<tr>
<td>280</td>
<td>69.14</td>
</tr>
<tr>
<td>108</td>
<td>26.67</td>
</tr>
<tr>
<td>28</td>
<td>6.91</td>
</tr>
<tr>
<td>91</td>
<td>22.47</td>
</tr>
<tr>
<td>53</td>
<td>13.09</td>
</tr>
</tbody>
</table>

Table 4.5: Results of investigation into error sources

**Subtitle translation quality**

Although two subtitles may indeed be acceptable translations of each other (correct subtitle-level alignment), the quality of the translation greatly dictates word-level alignment accuracy. A human translator can translate a subtitle in accordance with both the visual and oral contexts in which it appears. A non-literal translation for a subtitle may be concocted in order to convey a specific understanding for the context. Therefore, an authored subtitle may occasionally possess non-lexical or rare translations of expressions. The effect is that non-literal translations cause the alignment tool to calculate weak co-occurrence measures between word sequences, resulting in their misalignment.
Subtitle alignment tool

We used a subtitle alignment tool which aligns subtitles from two subtitle files based on character length and the timing information encoded within the files. The alignment program may err and incorrectly align subtitles which are not mutual translations, yet have similar length and are chronologically concurrent. Consequently, most word-level alignments will naturally be unsuccessful, meaning candidate MWEs will not be aligned and therefore not extracted. This, of course, is especially devastating for infrequent expressions.

Tagger and morphological analyzer/disambiguator

Errors resulting from tokenization, POS tagging, and morphological analysis and disambiguation tools are classified as preprocessing errors. Such an error manifests itself as an incorrect lexical or morphological analysis that has been assigned to a surface word. A correct morphological analysis is critical for the Text Isolation process because it determines the proper transformations to perform on the surface word form. An unintended transformation on a surface word may produce an inappropriate lemma form in the isolated output. As a result, this creates “noise”, weakening statistical co-occurrence measures between word sequences and therefore causing misalignments of candidate MWEs. For example, the noun-noun construct aiš mkirwut is translated as “salesman”. From the set of possible analyses given by the morphological analyzer, the morphological disambiguation tool mistakenly selects the analysis in which mkirwut (lit. “sales”) is analyzed as a verb meaning “they (female) recognize” instead. The transformation defined for verbs consequently outputs the word form hkir, the lemma of the verb meaning “to recognize”. Assuming that this error is incidental, any translation “salesman” will have a weak co-occurrence score with aiš hkir in comparison with that of the correct isolated form aiš mkirh.

Overaggressive Text Isolation

Our Hebrew-specific Text Isolation transformations were designed to deconstruct text to resemble our common standard. Instances in which transformations are “over-aggressive” generally exhibit abundant segmentation of numerous morphemes from their source word forms and greatly affect the
word-level alignment algorithm. In some English-Hebrew subtitle translations, splitting the individual morphemes of surface words into separate tokens in the isolated Hebrew may negatively impact the word-level alignment accuracy with the English. For lexical alignments in general, this negative impact could be expressed by segmenting Hebrew morphemes which have no correct alignment in the corresponding English subtitle. Also, in regards to MWE alignment, any MWE which is composed of many affixed morphemes will in turn be isolated and segmented into many tokens. The large size of the token sequence poses a problem for the word-level alignment tool because the more lengthy a sequence is, the more incapable the tool is of aligning them. For example, the Hebrew expression 

\[ bswp \tilde{s}l \ dbr \]  

(lit. “in the end of a thing”), “all in all”, is isolated to the form \[ b \ suwp \ \tilde{s}lw \ \tilde{s}l \ dbr \]. The alignment tool is incapable of making the five-token alignment necessary to capture this entire expression.

**Word-level alignment tool**

We employ a word sequence alignment algorithm which computes probabilities for correlated “translation units”, sets of one or more tokens in a sentence. Errors resulting from this word-level alignment tool are specifically caused by insufficient co-occurrence statistics. We attribute such errors to the following possible behaviors of the tool:

1. **Individually aligned MWE constituent tokens.** Some MWEs consist of word for word translations of each other. In such cases, the tool individually aligns each token which composes the MWE to its lexical translation. Therefore, the tool decides that 1:1 alignments are more correct than multi-token \( n:m \) alignments. For example, the tokens of the expression \( xiim \ mdp \), isolated from \( xii \ mdp \) (lit. “shelf life”), are aligned individually to their lexical counterparts. The tool determines that a stronger co-occurrence relationship exists between the single-token sequences \( xiim \) to “life” and \( mdp \) to “shelf” than exists between the multi-token sequence \( xiim \ mdp \) to “shelf life”.

2. **Shortest most correct partial alignment.** Partial MWE constituents which have a strong co-occurrence measure with a sequence in the source language. Therefore, the tool aligns that constituent, but leaves the
remaining constituents of the MWE unaligned. For example, the expression \(bn \text{ mšpxh}\) (“relative”) in the Hebrew sentence “ahbnw awtw kmw bn mšpxh” is translated in English as “we loved him like family”. The literal translation of \(mšpxh\) is “family”. Therefore, due to stronger co-occurrence measures, these two words are aligned to each other and the word \(bn\) is left unaligned by the alignment tool. The 1:1 alignment, rather than the 2:1, is calculated by the tool to be the most suitable alignment configuration.

3. **Partial incorrect alignment.** In such cases, not all of the constituent tokens of the MWE participate in the alignment. For example, the expression \(Twb lb\) should be aligned with “kindness” but only \(lb\) is aligned. We are not absolutely certain why the tool makes these errors. Although these errors might be related to overaggressive Text Isolation, we believe it is more attributed to be the fault of the tool’s probabilistic alignment scores.

4. **Incorrect alignment.** Some isolated MWEs are very infrequent and have weak co-occurrence measures with their translations. This leads to MWEs being misaligned or unaligned altogether and are therefore considered incorrectly aligned. For example, the expression \(anin T’m\) (“epicure”) only appears twice in the entire corpus with a different English translation in both instances. The tool is rendered unable to make the alignment to any tokens in the translations due to such weak cross-lingual co-occurrence statistics. In addition, the token \(anin\) does not appear anywhere else in the corpus except with \(T’m\) in those two occurrences while the word \(T’m\) is a very frequently occurring word often aligned with the English token “taste”. This understandably results in overall poor co-occurrence measures and leads to misalignment of the MWE.
Chapter 5

Conclusions

In this thesis we presented a methodology for identifying multi-word expressions and their translations from multilingual parallel corpora. By using our Text Isolation technique to decompose the morpheme composition of words, we showed that pre-processing surface word forms based on their lexical and morphological composition proves useful for identifying MWEs. From the original parallel corpus of English-Hebrew movie subtitle translations, we generated a new corpus by performing language-specific transformations on the word and morpheme content of each subtitle. We demonstrated an improvement in the ability of a word-level alignment algorithm to extract potential Hebrew MWEs at a higher precision from the “isolated” corpus over the original. Furthermore, we showed that Text Isolation encourages the alignment tool to make more accurate alignments to those MWEs. The addition of a third language (Spanish) to our methodology led to even further improvements in the identification of MWEs and their alignments.

Various extensions and adjustments to our work may be pursued. The morphological properties of the languages greatly impact the quality of the MWEs extracted from the isolated parallel corpora. Therefore, revising the Text Isolation transformations toward various common standards or even factoring in more languages or experimenting with languages with similar, or even different, morphologies could lead to better results. Our methodology was dependent on a word-level alignment tool which was shown in our error analysis (Section 4.4) to perform poorly in identifying certain MWEs. Among other weaknesses, the tool was not capable of aligning word sequences longer than three tokens. Re-training the language models
in order to encourage the alignment tool to make longer word sequence alignments will most likely prove useful for segmented transformed morphemes resulting from Text Isolation. Furthermore, the alignment algorithm may be re-engineered to simultaneously account for all languages in the parallel corpora. Meaning, it is possible to re-assess the aspect of the alignment algorithm which computes the co-occurrence statistics of the word sequences between translated sentences.
Appendix A

Text Isolation transformations

This appendix details the language-specific transformations defined and implemented for the Text Isolation methodology. The morphemes which comprise each source word are transformed into tokens according to their relevant classifications for all three languages used in the experiments (Hebrew, English and Spanish). Transformations are indicated by →.

A.1 Hebrew

- **Lemmatization.** The base morpheme of each source word is transformed to a token representing its base form as per its part-of-speech category.
  - Nouns are transformed to their singular form.
    - Example: dmwiwt → dmwt
  - Adjectives are transformed to their singular masculine form.
    - Example: gbwhwt → gbwh
  - Verbs are transformed to their past tense, third person, masculine, singular form. Particiles are transformed similarly.
    Examples:
    - mdbr → dibr
    - nknsti → nknst
Miscellaneous categories (pronoun, quantifier, interrogative, copula, negation, conjunction, interjection, punctuation, proper name, etc.) are transformed to their identical base morpheme form which is usually identical to the surface form detached from affixed morphemes.

Examples:
- ani → ani
- wkmh → kmh
- wmnmti → mti

Prefixes. Each prefixed bound morpheme \((w,b,m,l,k,š,kš)\) is detached from the source word and transformed into an individual token. The resulting segmented token order corresponds to the morpheme order of source.

Examples:
- bbit → b bit
- wkšbbit → w kš b bit

Determiner.

Nouns. The prefixed (or implied) bound determiner morpheme is detached from source word and transformed into the token \(h\).

Examples:
- hmšxq → h mšxq
- bbit → b h bit

Construct nouns. The determiner morpheme, which is attached to the last word in a noun construct, is detached and placed as an individual token \((h)\) before the first word in the construct. If the first word in the construct has prefixed morphemes, the detached determiner token is placed after the segmented morphemes and before the base form of the word.

Examples:
- txnt hmšTrh → h txnh mšTrh
- wilbit spr hšdh → w l h bit spr šdh
• **Suffixes.** The possessive bound morpheme suffix \((i,nw,k,km,km,wn,h,hm,hm,hn)\) ([SUFFIX]) is detached from the source noun ([NOUN]) and transformed into an individual token using the following template:

\[
[NOUN]+[SUFFIX] \rightarrow [NOUN] \sl +[SUFFIX]
\]

• Example: \(bitkm \rightarrow bit \sl km\)

• **Prepositions.** The prepositional word \((al,mn,acl,ld,kmw,lpni, l, l \ id, bin, b\,\,\,b\,\,\,b\,\,\,b, m, l, b)\) is transformed to a token representing its base form ([PREP]) followed by a token representing its attached object pronoun inflection ([OBJ]) using the following template:

\[
[PREP]+[OBJ] \rightarrow [PREP] awt+[OBJ]
\]

Examples:

• \(aclnw \rightarrow acl\,\,awtnw\)
• \(l\,\,lik \rightarrow l\,\,awtk\)
• \(l\,\,lidikn \rightarrow l\,\,id\,\,awtkn\)

### A.2 English

• **Lemmatization.** The base morpheme of each source word is transformed to a token representing its lemma as per its part-of-speech category.

• **Nouns** are transformed to their singular form.
  - Example: pencils \(\rightarrow\) pencil

• **Verbs** are transformed to their simple present first/second person form.

Examples:

• thinks \(\rightarrow\) think
• baking \(\rightarrow\) bake
• took \(\rightarrow\) take
• **Miscellaneous** categories (adjective, adverb, pronoun, preposition, quantifier, interrogative, negation, conjunction, interjection, punctuation, proper name, etc.) are transformed to their identical base morpheme form which is usually identical to the surface form of the source word.  
Examples:
- and → and
- quick → quick
- quickly → quickly
- him → him
- mine → mine

### A.3 Spanish

- **Lemmatization.** The base morpheme of each source word is transformed to a token representing its lemma as per its part-of-speech category.

  - **Nouns** are transformed to their singular form.
    - Example: papeles → papel
  - **Adjectives** are transformed to their singular masculine form.
    - Example: gordos → gordo
  - **Verbs** are transformed to their infinitive form.
    - Example:
      - creo → creer
      - entendiendo → entender
      - fuimos → ir
      - querrán → querer
  - **Miscellaneous** categories (pronoun, preposition, quantifier, interrogative, negation, conjunction, interjection, punctuation, proper name, etc.) are transformed to their identical base morpheme form which is usually identical to the surface form of the source word.
Examples:

- para → para
- yo → yo
- quién → quién

**Suffixes.** Each object pronoun morpheme suffix is detached from the source verb and transformed into an individual token. Either a 1. direct object \((me, te, lo, la, nos, os, los, las)\) \([\text{D OBJ}]\)) or an 2. indirect object \((me, te, le, nos, os, les)\) \([\text{I OBJ}]\)) followed by a direct object may be suffixed to a verb \([\text{VERB}]\). These cases are transformed using one of the following appropriate templates:

\[
\text{[VERB]+[D OBJ]} \rightarrow \text{[VERB] [D OBJ]}
\]
\[
\text{[VERB]+[I OBJ]+[D OBJ]} \rightarrow \text{[VERB] [I OBJ] [D OBJ]}
\]

Examples:

- comprándolas → comprar las
- dámelo → dar me lo
Bibliography


פירוק הרבונים המורפולוגיים והלקסיקליים בבסיס ליידי ביטויים

dניאל הורביץ
פירוק הרכיבים המורפולוגיים
המקסיקליים במילים לבר傾 גם ביטויים

חיבור על מחקר

לשם מילוי חלקי של הדרישות לקבלת התואר
מוניטור למדעי המחשב

דניאל הורביץ

הנהלת הטכניון – מכון טכנולוגי לישראל
2012 אונסנט בחיפה אונסנט 2012
המחק נועד להנחות אך, עם זאת, הוא גם ממחיש את מעלות חיקויים ונטיעות של התוכן.

המחたら במנוחה של פילוסוף, פילוסוף, על הסבלנות העינית וה חברות.

הערכתי מצור על עיסוק בברק דנוב פניקו של שפה טבועית. דוגמאות אלו הובילו
לעתים קרובות לשיחות בנושאים שונים: תרבות, פיסכונאות החילוף וחיקוי התוכנות

veloper, על פנים. אני מודע להוריו, מיכאל ואורל, על העידודה וה💖 של מתמטיקאים
ופסקת בלב хочי. אני מודע גם ללילדיבי פליבורד ו Lolita. הם הינו בתכנון
ההרופטאו שלארח ליימוי התוכנות המאורת וה访谈 contestants: ישראלי, לי

כאמור, אני מודע להוריו, לילדה, ולהואר. אני מודע גם לuento, על העידוד של לילדה
והSetText-ליילדה על מאמץ האופטימיות התוכנות של שיקולה של פירותי: "מעי
איפו"" שלא, לילדה, לינו לפניים בים, על ספינקס או רוחה בברית וממשישות שברכת

כל זה שלטدني בילומדי מוספכים.

אני מודע להוריו, (ולונגר ישראלי ובעלה), על התוכנות הנסוליות והברית קשרים.
שקפה תכונת ייחודית בודר לכל כמswick STN או במלות. גםпотребיomed או מונחים STN או במלות שהם
מתוים בחירת שייך STN או במלות. הנחיה STN או במלות שלמרכיבים זהב_ac est
במיוחד STN או במלות שלמרכיבים זהב-ac est של STN או במלות שלמרכיבים זהב-ac est
sense de la proposition est que ce STN ou ce STN est une proposition STN ou ce STN est une proposition STN.


 Tecnion - Computer Science Department - M.Sc. Thesis  MSC-2012-20 - 2012
It is possible to express "the" in English as background and in your houses. The synthetic English expression, for example, the Hebrew word, can be expressed in English as a stem, to which a court, a court, and a court, or, conversely, a court, a court, or, conversely, a court, can be added to the morphological root of the word. The operation can result in a change in the lexical root. For example, the word "the" is changed to "the", and the word "the" is changed to "the".

In addition to the stem conversion, the stem may be changed to a stem. This operation can result in a change in the root and in the word. For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the". For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the".

The goal of this research is to build an automatic Hebrew-English word translation system. In this way, we can apply the morphological component of the word in the Hebrew word. For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the". For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the".

In order to express the concept of a word, we use statistical methods. Statistical methods are used to calculate the frequency of occurrence of words in a corpus. In addition, statistical methods are used to calculate the frequency of occurrence of words in a word (or a word class). For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the". For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the".

The statistical methods used in this research are statistical analysis methods, statistical methods, and statistical methods. In addition, we use statistical methods to calculate the frequency of occurrence of words in a corpus. For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the". For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the".

In order to express the concept of a word, we use statistical methods. Statistical methods are used to calculate the frequency of occurrence of words in a corpus. In addition, statistical methods are used to calculate the frequency of occurrence of words in a word (or a word class). For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the". For example, in English, the word "the" is changed to "the", and the word "the" is changed to "the".
היווצרו דילולות נخطوطים – אם יצור מילה לא ת phận מספים פגמים כ‐ שיני שוחת אוالت

בשיטות סטטיסטיות.

ובобще לב הזפה, הוא דילול הנخطوطים הנובע מmonto שמותוף דילול הנ泅ית של השפה. גם מראים שונים בין תרגים פרגמולוגית ותרגומית של השפה. הנחת השון של השפה, היסוד של העצם רצף המילים בשפתה,แสง של י_quad ששפיט פגמים של דילול הבוררתرأسית השפה

ההבןת המשפט של סיכום יorraine בצה או תורגם של למופדים usado בפורמט של נילור חסיה.

במחקר זה, אנומביאים אלגוריתם לשיתוף בעברית闸ור שופליי. השיטה הזומת בפעולה אוטומטית חלוצית. את metodologia של נתיבינו היא אוטומטית שמלשון במלשון

יש נמצאות בפניה, 1,055 מקוונים של 1,055 ספרים של ספר

המבנים בסיסיים בתוכנית וגביו שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שמות שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקנט וeggies שבין שלパイ מוסר, מותרים בקantu
The document contains a detailed explanation of a method involving morphological analysis and transformation, specifically in the context of Hebrew language processing. The text discusses the creation of a new corpus by applying morphological transformations to an existing corpus. The transformations involve identifying and breaking down words, and then reassembling them to form a new corpus. The method aims to improve the accuracy of translation and identification of morphological units.

The transformed corpus is then evaluated against the original corpus to measure improvements in terms of accuracy and recall. The text mentions the use of an algorithm to match words between the transformed and original corpora, and includes a discussion on the effectiveness of the method.

The text also includes a section on the comparison of results between different morphological analyses, highlighting the improvements achieved. It mentions the use of a specific tool or technique for the analysis, and includes some figures or tables that are not visible in the text.

In conclusion, the document provides a comprehensive overview of the method and its application, demonstrating the potential benefits of morphological analysis in Hebrew language processing.
The fonts that were used in this text are Times New Roman (for the main text) and Arial (for the headings and some other elements). The size of the fonts is 12 for the main text and 14 for the headings.

The text is written in Hebrew and English. The English text is a translation of the Hebrew text. The translation is accurate and conveys the meaning of the original text.

The text is divided into sections, each with a title in Hebrew. The titles are bold and italicized. The text is justified and aligned left.

The text is written in a formal style, typical of academic writing. The sentences are concise and to the point.

The text is written in a consistent style throughout, with a clear structure. The paragraphs are well-organized, and the transitions between them are smooth.

The text is written in a professional tone, appropriate for a thesis. The language is clear and easy to understand.