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MASTER THESIS

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Entity Relationship Extraction

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Dedication.

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Introduction

This thesis researches relationship extraction in Czech. Relationship extraction is the task of extracting semantic relationship from a text. It is closely connected to named entity recognition, the task of tagging entities in text with their corresponding type, and entity linking, the task of disambiguating named entities to a knowledge base. If all those task are used together, we could gain knowledge databases automatically from text.

For English multiple attempts were made to solve or at least advance in relationship extraction, varying both in task assignment and in used technologies.

To be able to approach this set of tasks, we will focus on pure relationship extraction and thus the following restriction: we will only extract relations from sentences with labeled subject and object for the potential relation. We will benefit from the state-of-the-art technologies such as BERT from Devlin et al. [2018].

A key role in modern machine learning play datasets. In major part of this thesis, we will address the absence of a Czech dataset for relationship extraction. We will generate our dataset by aligning Wikidata¹ with Czech Wikipedia². This type of aligning is sometimes referred to as distant supervision. We will also need to recognize entities includes other . We will than be able to train different models and we will also be able to discuss how choices made in dataset generation affect the ability of a model to learn.

Given the absence of a dataset, we also deal with an absence of a baseline for model performance. To show that, at least the proposed architecture and training method we used, are comparable to state of the art result we will perform the same training with English BERT and we will evaluate it on some well known English datasets.

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0.1 Thesis organization

This thesis is split into two parts. Before we dive into the first part, we will provide information that is relevant for this thesis, but is not part-specific, such as more details on relationship extraction, connected terminology and further motivation. We will briefly introduce the Czech language to explain why existing distant supervision methods were most likely not applied on Czech.

The first part will focus on datasets. We will present some existing supervised datasets, we will propose methodology for generating the dataset via distant supervision and elaborate on the process of implementation and on the results we obtained.

In the second part, we will finally talk about the modern deep learning technologies, we will try to pinpoint the important aspects of models, etc. we are using. **Vysvětlíme, jaké metriky se používají a proč a v čem je s nimi problém. Natrénujeme a zkusíme interpretovat výsledky.**

¹<https://www.wikidata.org/wiki/>

²<https://cs.wikipedia.org/wiki/>

divná
věta

previous
work:
Ex-
isting
work on
relation
extrac-
tion
(e.g.,
Zelenko
et al.,
2003;
Mintz
et al.,
2009;
Adel
et al.,
2016)

which
meth-
ods,
were
they
not?

co víc
tam je

Přesunout We will use the Transformers³ library which makes training well-known pre-trained models accessible.

whatever
prostě
to
nejdřív
udělej,
pak o
tom piš

³<https://github.com/huggingface/transformers/>

1. Relationship extraction intro

This thesis is split into two parts that focus on different aspects of relationship extraction in the Czech language. In this section we provide a glossary of some NLP and relation extraction terms, we elaborate on the task itself and we include an introduction to the Czech language for non Czech readers.

změnit
název

1.1 Terminology

Terminology in NLP subtasks is often not exact or non-standardized. We will attempt to introduce the most important concepts for our work as exactly as possible while respecting the terms that seem to be already established.

Relation in this context is an abstraction of a semantic relation, for example a father relation. Relation is of a type (father) is binary (between the son and the father) and oriented (the father and the son are not interchangeable), and describes the relationship between a subject (the son) and an object (the father). We will use the term relation as an equivalent for its type and the term relationship for an instance of the relation.

hloupá
věta

někam
zapra-
covat
příklad
na větě,
jak je
nejdřív
najít
rozštěpení
a tak
všechno

obrázek
pro
příklad
v
dalším
odstavci

Subject and Object. The subject is the first argument of a relation, the object is the second. In the sentence “Albus Severus is Harry Potter’s son.” a relation of type SON is captured, the subject is Harry and the object is Albus Severus. The reasoning for this choice of direction is as follows: suppose we are gathering information about Harry, then we would probably have both the information that his son is Albus Severus and that his father is James. So we are gathering information about the subject (Harry Potter), even though in most sentences Harry is likely to be the grammatical object: “James is Harry’s father.” We will use the notation $\text{RELATION}(\text{subject}, \text{object})$: $\text{SON}(\text{Harry Potter}, \text{Albus Severus Potter})$.

will we,
lepší
vzhled

Both the subject and the object can generally be any word or sequence of words that represent concepts that have the ability to form relations. In some cases subjects, objects, or both are limited to entities or named entities.

Named entity is a real-world object, such as persons, locations, organizations, products, etc., that can be denoted with a proper name. Named entities can simply be viewed as instances (e.g., New York City is an instance of a city) of some concept - **class**. Sometimes, numeric data is considered in this category as well (for example by Named Entity Recognition tools). An **entity** is a named entity whose proper name is unknown or unimportant but still is an instance. (The word book can represent an abstract concept - class as well as entity.)

ukradeno
z wiki,
ocitovat
nebo
ukráct
od
jinud

Relation inventory is the set of relations, that are considered valid for a given dataset or model.

Positive relation mention is a sentence, that captures a relationship: a relation together with a tagged subject and object. We will omit the word positive unless we want to emphasize the fact.

Negative mention is close to relation mention in the sense that it is a sentence with tagged subject and object, but the relation type is one of these types:

- OTHER - human annotator would classify a relation, that is not in inventory.

- NO RELATION - in this case, human annotators should feel an absence of a relationship between a subject and an object.

NO RELATION comes with difficulties. Since there is no semantic relationship between subject and object, it makes it harder to choose subject-object pairs. It is probably desirable to have subject-object pairs, that could be related in a different sentence.

Relationship Extraction

doplnit
příklady
včetně
vyložení
ne
příkladu

znímit
entity z
názvu

1.2 Relationship Extraction

The relationship extraction task concentrates on prediction relationships. In the typical setup the task is to predict a relation type based on a sentence with two tagged entities. Variations of this exists, for example, in real life applications, the goal might be to output set of relationship based on a longer piece of text (and therefore the extractor would have several sentences mentioning the same entities).

Since the input for a relationship extraction model should contain tagged entities, a pipeline of an entity tagging tool and relationship extraction model would be necessary to perform relationship extraction on real data.

We are aware of two sources of motivation for relationship extraction. First, it can be an alternative for a summarization tool. And therefore it could be used anywhere where people are required to read long texts in short amount of time. In the second usecase, the extractor could convert texts into structured data and therefore build a database of relationships. For both applications, an entity linking tool would be beneficial (such a tool disambiguates named entities to a knowledge base) to eliminate confusion of similarly named entities.

Since many applications are likely to benefit from entity disambiguation, a pipeline of named entity recognizer, entity linker and finally relationship extraction would potentially be useful.

1.3 Czech language

One of the objectives of this thesis is to work with Czech language, therefore we find it useful to make some notes on Czech (for non-Czech speaking readers). Czech is a Slavic language with rich morphology and relatively free word order. Most of Czech morphology can be treated with a morphological analyzer, still, it might be useful to have a better understanding of the language we will work with.

1.3.1 Inflection

In Czech, nouns, adjectives, pronounce and numerals are declined. The inflection expresses (not necessarily unambiguously) one of seven cases and a number (singular or plural). Any inflected word in Czech has a grammatical gender, for words, that have natural gender, those two genders align: “žena” (*woman*) is feminine and “muž” (*man*) is masculine. The inflection of each declinable word

singular				
	masculine animate	masculine inanimate	feminine	neuter
nominative	příčný		příčná	příčné
genitive	příčného		příčné	příčného
dative	příčnému		příčné	příčnému
accusative	příčného	příčný	příčnou	příčné
vocative	příčný		příčná	příčné
locative	příčném		příčné	příčném
instrumental	příčným		příčnou	příčným
plural				
	masculine animate	masculine inanimate	feminine	neuter
nominative	příční	příčné	příčná	
genitive	příčných			
dative	příčným			
accusative	příčné			příčná
vocative	příční	příčné	příčná	
locative	příčných			
instrumental	příčnými			

	singular	plural
nominative	ulice	ulice
genitive	ulice	ulic
dative	ulici	ulicím
accusative	ulici	ulice
vocative	ulice	ulice
locative	ulici	ulicích
instrumental	ulicí	ulicemi

(a) Declension of “příčný” (diagonal)

(b) Declension of “ulice” (street)

Figure 1.1: Examples of czech declension, taken from Wiktionary.

follows a pattern. This all means that a single word (lemma) can have a lexeme of size

kolik?

Verbs are conjugated, the conjugation expresses person, numeral, tense, voice, and mode. Verbs follow one of 14 patterns. An average Czech either finds the theory about Czech verbs and tenses confusing or is even unaware of the existence of the verb patterns. That likely contributes to commonly incorrectly used forms of verbs even in the official language.

An important aspect of declension for us is agreement. In English, subject and verb agree (limited just to the third person). In Czech, subject and verb also agree, but in noun phrases there needs to be an agreement as well.

We include an example to help grasp those concepts to readers who do not speak any inflexive language. In figure XX words “příčný” (diagonal) and “ulice” (street) are declined, the noun phrase “Příčná ulice” is Czech equivalent of the Diagon Alley. The lexemes sizes are 11 and 7, so combinatorically, the noun phrase could have 77 forms. As we explained, in Czech, there is a agreement in noun phrases, and only 9 different forms of the noun phrase “Příčná ulice” are valid.

příklad:
toho,
jak je
nějaká
noun
phrase,
počet
lexémů,
počet
validních
...

1.3.2 Word order

Unlike in english, the sentences structure is relatively relaxed in Czech. The basic sentence structure is of SVO (subject verb object) type but even when the word order is completely different, the sentence might still be understandable thank to the inflected forms of words. At the same time, the word order is not arbitrary, some orderings of words do not form a valid sentence. Those, that are valid can carry different message (completely different, with different emotion, different emphasis and so on).

odkaz
dopředu
kde
řeším,
jak
matcho-
vat

The position of attributes tends to be mostly fixed, some are prepositive, some postpositive, but most of them stays the same (within the noun phrase) unless some sort of enumeration is used. If we return to the “Příčná ulice” example, we are not able to recollect a sentence, where the reversed order is used and no other “ulice” is mentioned.

Part I

Datasets

2. Existing datasets

In this chapter, we will overview well-known datasets related to Entity Relationship Extraction. We will start with supervised datasets (SEMEVAL 2010 task 8 and TACRED), then we will focus on distant supervision.

tady
představíme
exis-
tující
dataasty

2.1 SEMEVAL 2010 task 8 dataset

The SemEval-2010 Task 8 dataset (S10T8) was introduced in SemEval-2010 Task 8: Multi-Way Classification of Semantic Relations Between Pairs of Nominals Hendrickx et al. [2010]. We will summarize how S10T8 was created and some other information from that article so that later we can compare different approaches.

The authors started by choosing an inventory of semantic relations. They aimed for such a set of relations that it would be exhaustive (enable the description of relations between any pair of nominals) and mutually exclusive (given context and a pair of nominals only one relation should be selectable). Chosen relations with descriptions and examples are listed in table 2.1.

nějak
napsat,
že
nebudu
citovat,
ale
je to
hodně
vykradené?

They decided to accept as relation arguments any noun phrases with common-noun heads not just named entities or some other specific class of noun phrases, mentioning 'Named entities are a specific category of nominal expressions best dealt with using techniques which do not apply to common nouns.' But they restricted noun phrases to single words with the exception to lexicalized terms (such as science fiction).

proč
není
table
součást
od-
kazu?

nechat
ut tu
citaci?

quote
better

formát

The annotation process had three rounds. In the first round, authors manually collected around 1,200 sentences for each relation through pattern-based Web search (with at least a hundred patterns per relation). This way, they obtained around 1200 sentences for each relation. In the second round, each sentence was annotated by two independent annotators. In the third round disagreements were resolved and the dataset was finished. Every sentence was classified either as a true relation mention or was a near-miss and thus classified as "other", or was removed.

lepší
uvo-
zovky

The dataset contains of 10717 relation mentions. For the original competition, teams were given three training dataset of sizes 1000 (TD1), 2000 (TD2), 4000 (TD3), and 8000 (TD4). There was a notable gain TD3 → TD4 therefore the authors concluded that even larger dataset might be helpful to increase performance of models. But

.. that is so much easier said than done: it took the organizers well in excess of 1000 person-hours to pin down the problem, hone the guidelines and relation definitions, construct sufficient amounts of trustworthy training data, and run the task.

2.2 TACRED dataset

The TAC Relation Extraction Dataset was introduced in Zhang et al. [2017]. TACRED is a supervised dataset obtained via crowdsourcing. It contains about

Table 2.1: S10T8 summary. List of relations, their official descriptions, a random example and both relative and absolute count.

CAUSE-EFFECT	12.4%
An event or object leads to an effect.	(1331)
Example: <i>The <u>burst</u> has been caused by water hammer <u>pressure</u>.</i>	
INSTRUMENT-AGENCY	6.2%
An agent uses an instrument.	(660)
Example: <i>The <u>author</u> of a <u>keygen</u> uses a <u>disassembler</u> to look at the raw assembly code.</i>	
PRODUCT-PRODUCER	8.8%
A producer causes a product to exist.	(948)
Example: <i>The <u>factory</u>'s products have included flower pots, Finnish rooster-whistles, pans, <u>trays</u>, tea pots, ash trays and air moisturisers.</i>	
CONTENT-CONTAINER	6.8%
An object is physically stored in a delineated area of space.	(732)
Example: <i>This cut blue and white striped cotton <u>dress</u> with red bands on the bodice was in a <u>trunk</u> of vintage Barbie clothing.</i>	
ENTITY-ORIGIN	9.1%
An entity is coming or is derived from an origin (e.g., position or material).	(974)
Example: <i>The <u>avalanches</u> originated in an extensive <u>mass</u> of rock that had previously been hydrothermally altered in large part to clay.</i>	
ENTITY-DESTINATION	10.6%
An entity is moving towards a destination.	(1137)
Example: <i>This book has transported <u>readers</u> into <u>ancient times</u>.</i>	
COMPONENT-WHOLE	11.7%
An object is a component of a larger whole.	(1253)
Example: <i>The system as described above has its greatest application in an arrayed <u>configuration</u> of antenna <u>elements</u>.</i>	
MEMBER-COLLECTION	8.6%
A member forms a nonfunctional part of a collection	(923)
Example: <i>The <u>student association</u> is the voice of the undergraduate student population of the State University of New York at Buffalo.</i>	
MESSAGE-TOPIC	8.4%
A message, written or spoken, is about a topic.	(895)
Example: <i>Cieply's <u>story</u> makes a compelling <u>point</u> about modern-day studio economics.</i>	
OTHER	17.4%
	(1864)
Example: <i>The <u>child</u> was carefully wrapped and bound into the <u>cradle</u> by means of a cord.</i>	

100 000 examples.

The authors are relatively brief about the data collection process:

We create TACRED based on query entities and annotated system responses in the yearly TAC KBP evaluations. In each year of the TAC KBP evaluation (2009–2015), 100 entities (people or organizations) are given as queries, for which participating systems should find associated relations and object entities. We make use of Mechanical Turk to annotate each sentence in the source corpus that contains one of these query entities. For each sentence, we ask crowd workers to annotate both the subject and object entity spans and the relation types.

TACRED relation inventory captures only relations with subject being an organization or a person. Objects are of following types: cause of death, city, country, criminal charge, date, duration, ideology, location, misc (used for alternative name relation and no_relation only), nationality, number, organization, person, religion, state or province, title and url.

TACRED was designed to be highly unbalanced. 79.5% of data is the no_relation relation, which should be closer to real-world text and supposedly should help with not predicting false positive. However even if we look only at actual relations, there are vast differences in frequency: top six relations make up half the dataset and bottom six less than 2%. In absolute numbers the least common ord:dissolved relation has only 33 examples and median is only 286 examples.

Table 2.2: TACRED summary. List of relations, their official descriptions, a random example and both relative and absolute count.

NO_RELATION	79.5%
Example: “ <i>One step at a time</i> , ” said Con Edison spokesman Chris Olert in Sunday editions of <i>The Daily News</i> .	(84490)
ORG:ALTERNATE_NAMES	1.3%
Example: <i>The ARMM was established as a result of the peace agreement between the government and the <u>Moro National Liberation Front</u> -LRB- <u>MNLF</u> -RRB- in 1996 .</i>	(1358)
ORG:CITY_OF_HEADQUARTERS	0.5%
Example: <i>Once completed , the cuts will leave the <u>Irvine</u> , California-based <u>Option One</u> subsidiary with about 1,400 employees .</i>	(572)
ORG:COUNTRY_OF_HEADQUARTERS	0.7%
Example: <i>The Review based its report on a new survey conducted by the <u>International Agency for Research on Cancer</u> in Lyon , <u>France</u> .</i>	(752)
ORG:DISSOLVED	0.0%
Example: <i>News Corp. sold its satellite television service <u>DirecTV</u> in <u>2008</u> to <u>Liberty Media</u> .</i>	(32)
ORG:FOUNDED	0.2%
Example: <i>New York-based <u>Zirh</u> was founded in <u>1995</u> and makes products using natural oils and extracts .</i>	(165)
ORG:FOUNDED_BY	0.3%
Example: <i>The <u>Jerusalem Foundation</u> , a charity founded by <u>Kollek</u> 40 years ago , said he died of natural causes Tuesday morning .</i>	(267)
ORG:MEMBER_OF	0.2%
Example: <i>Lyons and the <u>Red Sox</u> say they are n’t aware of any other <u>Major League Baseball</u> team with such an arrangement .</i>	(170)

ORG:MEMBERS	0.3%
Example: <i>The NFL refused to abandon the city , and the <u>Saints</u> won the <u>NFC South</u> in 2006 , their first season with Brees and Payton .</i>	(285)
ORG:NUMBER_OF_EMPLOYEES/MEMBERS	0.1%
Example: <i>Established in September 1969 , the <u>organization</u> now has <u>57</u> member states worldwide .</i>	(120)
ORG:PARENTS	0.4%
Example: <i>The initial offering of AIA raised \$ 178 billion for AIG , while the sale of <u>ALICO</u> to <u>MetLife</u> reaped about \$ 155 billion .</i>	(443)
ORG:POLITICAL/RELIGIOUS_AFFILIATION	0.1%
Example: <i>Manila signed a peace treaty with the <u>MNLF</u> in 1996 , ending a decades-old separatist campaign in return for limited <u>Muslim</u> self-rule .</i>	(124)
ORG:SHAREHOLDERS	0.1%
Example: <i>Stop the NAACP and <u>Al Sharpton</u> 's <u>National Action Network</u> from committing this disgrace in our community .</i>	(143)
ORG:STATEORPROVINCE_OF_HEADQUARTERS	0.3%
Example: <i>Learn More <u>Chelsea District Library</u> 221 S Main St Chelsea , <u>MI</u> 48118 -LRB- 734 -RRB- - 475-8732 Find it on a map</i>	(349)
ORG:SUBSIDIARIES	0.4%
Example: <i>The new law will also enable the government to take over <u>Austral Lineas Aereas</u> , an <u>Aerolineas Argentinas</u> subsidiary .</i>	(452)
ORG:TOP_MEMBERS/EMPLOYEES	2.6%
Example: <i>Earlier this year , <u>Anatoly Isaikin</u> , head of <u>Rosoboronexport</u> , said Russia still considers Iran a valuable arms customer .</i>	(2769)
ORG:WEBSITE	0.2%
Example: <i><u>Swiss Bankers Association</u> : http://www.swissbanking.org</i>	(222)
PER:AGE	0.8%
Example: <i>Doctor <u>Carolyn Goodman</u> , Rights Champion , Dies at <u>91</u></i>	(832)
PER:ALTERNATE_NAMES	0.1%
Example: <i><u>Remy Ma</u> , whose real name is <u>Remy Smith</u> , is charged with first - degree assault and other charges .</i>	(152)
PER:CAUSE_OF_DEATH	0.3%
Example: <i>The cause was <u>kidney failure</u> , said a spokesman for the <u>Ali Akbar College of Music</u> .</i>	(336)
PER:CHARGES	0.3%
Example: <i>Actor <u>Danny Glover</u> has been convicted in Canada for <u>trespassing</u> in a hotel during a union rally in 2006 .</i>	(279)
PER:CHILDREN	0.3%
Example: <i><u>Al-Hakim</u> 's son , <u>Ammar al-Hakim</u> , has been groomed for months to take his father 's place .</i>	(346)
PER:CITIES_OF_RESIDENCE	0.7%
Example: <i>As part of a Navy family , <u>she</u> also lived in Long Beach , Calif. , San Diego and <u>Annapolis</u> .</i>	(741)
PER:CITY_OF_BIRTH	0.1%
Example: <i><u>Jane Matilda Bolin</u> was born on April 11 , 1908 , in <u>Poughkeepsie</u> , NY .</i>	(102)
PER:CITY_OF_DEATH	0.2%
Example: <i>The statement was confirmed by publicist Maureen O'Connor , who said <u>Dio</u> died in <u>Los Angeles</u> .</i>	(226)
PER:COUNTRIES_OF_RESIDENCE	0.8%
Example: <i>His wife , who accompanied Yoadimnadj to Paris , will repatriate <u>his</u> body to <u>Chad</u> , the ambassador said .</i>	(818)

PER:COUNTRY_OF_BIRTH	0.0%
Example: <i>CARACAS , Jan 10 -LRB- Xinhua -RRB- <u>Hugo Chavez</u> , was born on July 28 , 1954 , in <u>Venezuela</u> 's Sabaneta .</i>	(52)
PER:COUNTRY_OF_DEATH	0.1%
Example: <i>Egypt 's state-owned Middle East News Agency said <u>Tantawi</u> died in <u>Saudi Arabia</u> , where he attended a religious ceremony .</i>	(60)
PER:DATE_OF_BIRTH	0.1%
Example: <i>Antonioni was born in <u>1912</u> in the northern Italian city of <u>Ferrara</u> .</i>	(102)
PER:DATE_OF_DEATH	0.4%
Example: <i><u>December 6 , 2007</u> <u>Jefferson DeBlanc</u> , Hero Pilot , Dies at 86 By RICHARD GOLDSTEIN</i>	(393)
PER:EMPLOYEE_OF	2.0%
Example: <i>He and his group also joined in a legal battle challenging the <u>Washington Redskins</u> ' trademarked name .</i>	(2162)
PER:ORIGIN	0.6%
Example: <i>French media are reporting that <u>French</u> tennis player <u>Mathieu Montcourt</u> had died at the age of 24 .</i>	(666)
PER:OTHER_FAMILY	0.3%
Example: <i>In the interview <u>Cunningham</u> acknowledged the fragility of <u>his</u> choreographic record .</i>	(318)
PER:PARENTS	0.3%
Example: <i>The outgoing governor of Barinas is <u>Hugo de los Reyes Chavez</u> , father of <u>Hugo</u> and Adan Chavez .</i>	(295)
PER:RELIGION	0.1%
Example: <i>He closed out the quarter making seven payments to <u>Scientology</u> groups totaling \$ 13,500 .</i>	(152)
PER:SCHOOLS_ATTENDED	0.2%
Example: <i>She graduated from <u>Mount Holyoke College</u> in 1941 and from the Yale School of Law in 1948 .</i>	(228)
PER:SIBLINGS	0.2%
Example: <i><u>Raul Castro</u> , <u>Fidel</u> 's younger brother , has made several overtures toward Washington .</i>	(249)
PER:SPOUSE	0.5%
Example: <i>After returning to Dothan in 1946 , <u>Flowers</u> married <u>Mary Catherine Russell</u> .</i>	(482)
PER:STATEORPROVINCE_OF_BIRTH	0.1%
Example: <i><u>Thomas Joseph Meskill Jr</u> was born in New Britain , <u>Conn</u> , on Jan 30 , 1928 .</i>	(71)
PER:STATEORPROVINCE_OF_DEATH	0.1%
Example: <i>Jessica Weiner says <u>Greenwich</u> died of a heart attack at St. Luke 's Roosevelt Hospital in <u>New York</u> .</i>	(103)
PER:STATEORPROVINCES_OF_RESIDENCE	0.5%
Example: <i>Sen. <u>Chris Dodd</u> of <u>Connecticut</u> has proposed taxing polluters for their carbon emissions .</i>	(483)
PER:TITLE	3.6%
Example: <i>He is the founder and leader of Architects and Engineers for 9/11 Truth -LRB- AE911Truthorg -RRB- .</i>	(3861)

2.3 Riedel NYT dataset

The previous two datasets were obtained through a tedious human labour - human annotators went through texts and manually annotated the data. This process is slow and expensive, which explains the relatively why the datasets are relatively small. In this section, we will introduce a dataset that was presented in XX and that was created without the need for any additional manual annotation.

This dataset was generated with the distant supervision approach. This approach is based on aligning structured data (knowledge base) with text, i.e. automatically tagging mentions of the structured data in the text. In distant supervision, we usually expect that if there are two entity mentions in a sentence that are related, then the sentence expresses their relationship. The authors acknowledge that this assumption is often violated and they propose a methodology that attempts to predict whether the assumption is violated in a sentence. Using this methodology, they generated a dataset from the NYT Corpus and Freebase. We will refer to this dataset as Riedel NYT.

[link](#)

The dataset is divided into two parts, each of them containing a test set and a train set. We will use both train sets for training and the “heldout” test set for evaluation in the second part of this thesis.

Relation inventory for the part of the dataset that we used contains 58 relations. The best represented is the NA relation with XX%. The representation of relations varies between the train and test set. For example, there are two relations, that are not represented in the train set. Given the size of the relation inventory, we do not include an exhaustive table as we did with previous datasets.

3. CERED

In this chapter we will describe our process of generating **Czech Relationship Extraction Dataset (CERED)**. We will discuss various decisions that we made during this process and their impacts.

3.1 Overview

The objective is to use distant supervision to create a Relationship Extraction dataset for the Czech language. This section is a brief summary for easier orientation in this chapter. Each of these paragraphs is a teaser for one section of this chapter.

First we research available knowledge bases and Czech text corpora to determine which ones will best suit our purpose. We chose Wikimedia projects Wikidata and Czech Wikipedia.

Next we analyze how we will find mentions of Wikidata relations in Czech Wikipedia. We sketch out dataflow diagrams and we think about all the different complex aspects of this task.

We continue by choosing technologies that we use. Aware of the volume and other characteristics of chosen data, we choose Python as the main programming language, Spark as a way to speed up the computations and MorphoDita to deal with the specifics of the Czech language.

The questions and options that rose from the analysis get at least partially answered and decided during implementation. We tested different configurations and went through the data to determine what will work best. As a result, we generated CERED, or more exactly many different versions of CERED in search for the best one to use for training in the second part of this thesis.

Results

nějaká
návažnost
- říct,
že
popisují,
že budu
spo-
jovat
wikipedia

link
zpátky

results

3.2 Data sources

To be able to perform distant supervision we need to find suitable data - Czech text corpus and a knowledge base (Figure 3.1). In the first subsection, we will explain the requirements and constraints we have on such data and present our options. In the next two subsections, we will provide more information on the chosen ones.

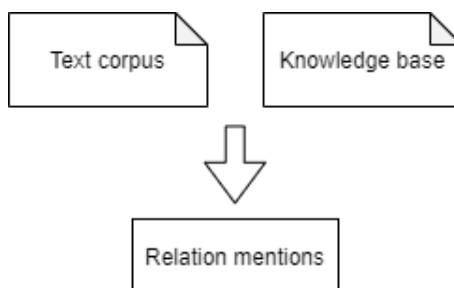


Figure 3.1: Distant supervision diagram

3.2.1 Constraints and requirements

The main constraint is quite straightforward, there has to be a nontrivial shared set of entities and relations mentioned in the text and stored in the knowledge base. We expect more fact-based texts to be more suitable, and therefore we will prefer encyclopedic or journalistic genre. One option is to focus on some subset of Czech National Corpus ¹, for example SYN2013PUB, SYN2009PUB, and SYN2009PUB are corpora of written journalism. The other option is to lean in the direction of encyclopedic text with Czech Wikipedia.

tak špatná věta

To the best of our knowledge, our options for knowledge base are limited to Wikidata or Google Knowledge graph ².

We decided to use Czech Wikipedia and Wikidata, mostly because the intersection of information expressed in text data and in structured data seems promising because they are build on each other. Another advantage could be the multilingualism of Wikimedia projects, and therefore the transferability of this work will be higher.

Další důvody, že jde stáhnout, že není black-box? lepší disambiguata

3.2.2 Czech Wikipedia

Wikipedia is a multilingual online encyclopedia created and maintained as an open collaboration project by a community of volunteers as defined in Wikipedia contributors [2020]. From our point of view, Wikipedia is a corpus of text with tagged topics of articles and some entity mentions. Czech Wikipedia contains approximately 440 000 articles and ranks top 30 across all the different language editions of Wikipedia.³

A dump of Czech Wikipedia is about 1,6GB and 770MB when compressed.

3.2.3 Wikidata

Wikidata is a knowledge base which acts as a central storage of the structured data of Wikimedia projects. Just like Wikipedia, this project is freely available and edited by users (and bots). It provides the option to query the database online (for small enough queries), but it is also possible to download the database in standard formats.

The database focuses on **items**, which represent objects, entities, concepts, etc. The first data collected in Wikidata were links to a multilingual version of Wikipedia articles on the same topic - on the same Wikidata item. Each item is assigned an identifier, prefix Q and a unique number, referred to as **QID**. A label together with a description of an item should serve as a human readable identifier. Labels, descriptions and optional aliases are language dependant.

Properties, another big concept of Wikidata, can be thought of as categories of items (*mother P25* implies a category of all mothers) or as relations between items (*Ron Weasley Q173998 has a mother P25 Molly Weasley Q3255012*). Each property has its **PID**, an identifier consisting of a prefix P and a unique number, and a data type for a value it can be paired with (such as an item, string, url, number or media file).

hezčí formátování wiki-itemm

¹<https://www.korpus.cz/>

²<https://developers.google.com/knowledge-graph>

³As of March 2020 according to https://en.wikipedia.org/wiki/List_of_Wikipedias

Information about any item is recorded in statements. Statement is a key-value pair of a property and a value of prescribed data type. For example, for *Ron Weasley* *Q173998* there are seven statements about his siblings:

- *sibling* *P3373* *Ginny Weasley* *Q187923*,
- *sibling* *P3373* *Fred Weasley* *Q13359612*,
- *sibling* *P3373* *George Weasley* *Q13359613* and so on

Wikidata project contains over 80 000 000 items, which raises requirements on technological resources so that we can work efficiently with such data. JSON dump of Wikidata takes 110GB of disk space or 37GB if bzip2 compressed.

formating

jiná slova

3.3 Analysis

The process of creation of CERED is mostly an attempt to execute the first two parts of the pipeline we mention in the first chapter. To the best of our knowledge, there is no suitable entity linking tool for Czech. There are tools for Named Entity Recognition that we could theoretically use to our advantage if we decided to focus on named entities only.

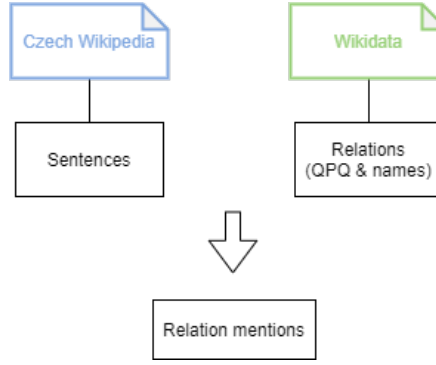
link

Therefore we need to find a way to get to similar results as the first stages of the pipeline would get. We do not expect that our CERED generator will be as powerful as the respective dedicated tools would be. We will not try to create general entity recognition and linking tools - on the contrary, we will exploit any extra information that chosen Wikimedia projects provide.

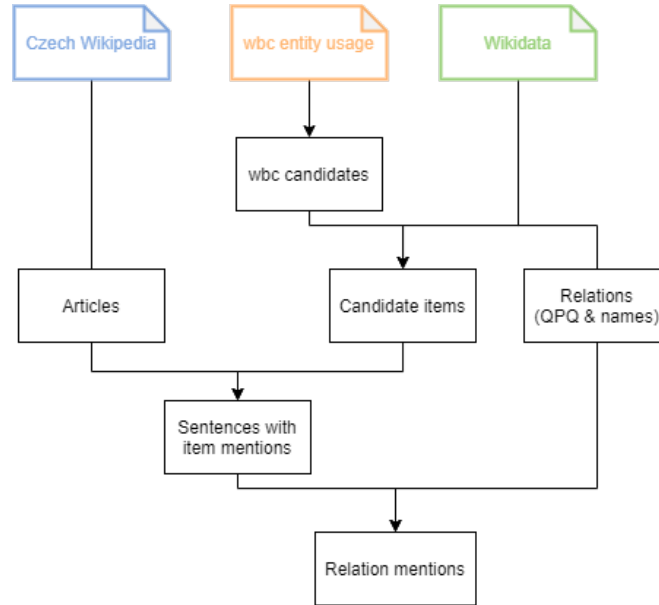
There are several aspects that we need to think through. We introduce them in the following list for better orientation. A subsection in this section is dedicated to each of those aspects.

úplně odstranit ten list?

- Dataflow - we chose Wikidata and Czech Wikipedia, but we did not discuss how to connect them and what exactly should be the outcome to be able to proceed to locating mentions.
- Entity Matching - suppose we collected a piece of text together with a set of entities that could be mentioned in the text. The process of entity matching attempts to mark words in the text that mention an entity.
- Wikilink mentions - Wikilinks are (mostly) human labeled entity mentions. Utilizing them is the closest we can get to a supervised dataset without actually supervising the dataset.
- Relation Matching - entities are matched, relationships are extracted, we use distant supervision assumption to locate relation mentions.
- Relation Inventory - we generated CERED, but the relation inventory is overly diverse. Moreover, the dataset is extremely unbalanced - the number of mentions per relation varies. And no “no relation” relation is obtained.
- Result Evaluation - every time we generate CERED during development, we need to evaluate its quality. We propose methods for this evaluation.



(a) Uninformed approach



(b) Informed approach

3.3.1 Dataflow

We start the whole process of creating our dataset with two files. The first file is a Czech Wikipedia dump. It is a collection of articles where each article has its title, id and text. And the other file is a Wikidata dump.

The simplest way of processing those files would be to process them separately and thus obtaining sentences on one side and relationships (a relation type with two items) on the other. This approach comes with a clear disadvantage. We would lose any additional information about the sentences that could be potentially useful (for example article title might be helpful to determine which items are mentioned in the sentence).

To solve this we could precompute something for each article and attach it to each sentence (article title, all Wikilinks in the article, etc.) risking a massive increase in required capacity to work with such data. On a similar note, we would probably process Wikidata to store item names (labels and aliases) for each relationship, worsening the situation even further.

We decided to update the dataflow to address those issues. We will preprocess Wikidata dump to contain only the data we will use. We will refer to this processed version of Wikidata as **custom Wikidata**. An item will be kept only if it

has a Czech name and we will significantly reduce its statements: we will keep the title of its Czech Wikipedia article and create a list of (QID,PID,QID) triples - **QPQ**, representing statements that contain information about relations between this item and the other items. This way, we have all the necessary information - article title to be able to connect an article to an item, names for each item to be able to find mentions of items and finally QPQ triples to connect relations and sentences. Moreover, custom Wikidata size is closer to traditional RAM size. Therefore we could for example load item names into memory, which will come in handy during the implementation.

One approach to finding item mentions in text could be called uninformed (Figure 3.2a). We could assume that any item can be mentioned in any sentence. This approach seems to have two issues: the computation would likely take quite some time but mainly we expect a huge amount of ambiguous mentions. An example of this ambiguity that we see as problematic might be children named after their parents. In this case, not only that the entities might get confused but also if we then assign the relation, we might easily confuse a sentence mentioning a spouse relation for a parent relation, which, unfortunately, is extremely challenging to solve.

On the other side, we can use the extra information that Wikimedia projects provide and opt for a more informed approach. A diagram of this approach is captured in 3.2b The topic of most Czech Wikipedia articles is a Wikidata item, therefore this item is nearly certainly mentioned in the article. Some Wikidata statements were based on relevant articles and thus it seems rational to expect items, that are related to the main item of an article, to be mentioned. We decided to look only for a tiny subset of all Wikidata items in each article - **candidate items**. As we just discussed, if an article is based on an item, then this item and all items, that are connected to it by a statement, are considered candidate items.

Czech Wikipedia maintains a **wbc** entity usage table, which contains information about which article uses which item. If we use this table, we are able to obtain a list of items, that should be mentioned in an article, let us call this list a **wbc candidates**. A **wbc** candidate is at the same time a candidate item.

We might consider adding even a second level of relatives (items related to items that are related to the main item) but the branching factor might be relatively high and cause unwanted ambiguity. Consider an instance item like a specific country, all countries would be second level relatives and thus a candidate item. Since countries tend to be of a certain type (kingdom, republic, state etc.) there might be simply the type or some other more general name amongst their names (Q30 United States of America are also known as America or United States) and more countries might share this name.

So far we mostly discussed the advantages of the proposed informed approach, mainly a hope for higher precision, specifically higher precision for item mentions. We should elaborate on some disadvantages as well. We are not trying to fully do entity linking. In the end we will only use item mentions, if the following condition holds: there are two entity mentions in one sentence and there exists a QPQ that connects them. It is debatable whether we need an informed approach to increase relation mention precision. The improbability that this condition will be fulfilled for false-positive item mentions might in fact be sufficient.

One more way to locate item mentions is through **Wikilinks**. A Wikilink links a page to another page within the same-language Wikipedia. First additional information this brings is simply the item mention (if the linked page or article has its main item). We can also consider the textual part of the link to be another name for the linked item. The quality and suitability of this name are to be examined and if we will find these names useful, they can be added to the item names we use.

sice by šlo neparalelně, ale co rychlost?

Mluvit o tom, proč nejdřív najdeme, co v článku hledat, pak to nasekáme na věty, pak matchujeme. Zmínit, kolik je jiných možností, že teoreticky by šlo ještě před rozsekáním na věty dělat entity linking ...

Detailně popsat, co kdy kam poteče + diagram

3.3.2 Entity matching

We have text on one side, gathered candidate items on the other and our goal is to find occurrences of these items in the text. We call this process **entity matching** and each found occurrence is an **entity mention**.

No matter how the matching will be done, it seems always beneficial to start the process with some text preprocessing. Quite a lot of changes need to happen even if some seem like little details. We will separate this preprocessing into a wiki specific part, lexical analysis and the last part is devoted to lexical analysis on standalone noun phrases.

When we eventually proceed to entity matching, there is a wide spectrum of complexity we might aim for. We are not trying to create a strong sophisticated tool for entity recognition and linking. We will describe some of those complexity tears and choose the right method for our use case.

Wikipedia parsing

Wikipedia parsing starts with an article in Wikitext and produces human-readable plain text - **clean text**. We should keep track of positions of Wikilinks from the Wikitext in the clean text.

Wikipedia is written in Wikitext (Wiki markup, Wikicode). This markup provides all usual functionalities such as determining the layout or fonts and enables commonly-used concepts like lists, links, media file insertion, or tables, and some more wiki specific concepts like infoboxes.

We plan on using one or even a combination of existing Wikitext parsers since each of them provides different functions.⁴ Therefore the parsing itself is not too troublesome.

One problem that needs to be addressed is what should we consider to be a valid text. For example, it is not clear how to work with tables. From one point of view, if we convert a table into an unstructured text, the text will not be a regular text in terms of sentence structure. From a different point of view, an unstructured text obtained by converting a table still contains information, that human readers will likely decode. Moreover, tables and other structured data tend to contain a lot of information. This will likely cause problems because we

⁴https://www.mediawiki.org/wiki/Alternative_parsers

Lord Voldemort (Tom Rojvol Raddle, Voldemort, Pán zla)

Figure 3.2: First paragraph from Czech Wikipedia page about Lord Voldemort Q176132, also known as Tom Rojvol Raddle, Voldemort, Pán zla (Dark Lord)

want to concentrate on sentence-like data, not just for example tuples of data that for example a table of athletes might provide (tuples of persons and countries). This kind of data might significantly damage the quality of CERED.

The elimination of all Wikipedia content, that is too structured or generally, not enough sentence-like, but at the same keeping as much as possible will be addressed later in XX. That way we can see the consequences of the eliminated and kept content.

Lexical Analysis

For our purpose keeping the text in long sequences of characters (such as an article) is not the best format. We need to parse those sequences into smaller tokens, such as words and sentences. A tool that addresses such tasks is usually called a **tokenizer**. Tokenization is a process that aims to split text (sequence of characters) into separate tokens. Naive tokenizer might just simply split on non-alphanumeric characters. But if the tokenizer is supposed to actually perform well and recognize sentences, a more sophisticated tool is needed. For this reason, we will outsource handling text to a Czech tokenizer called MorphoDiTa, that achieves state-of-the-art results for the Czech language. Using such a tool, we can convert clean text into sentences made up of tokens and we even obtain the lemma and lexeme of each token.

Lexical Analysis on Names

Tokenizers (and lemmatizers) are usually trained to perform well on sentences and might be inaccurate on noun phrases when they stand alone, as entity names do. If we were determined to tokenize them, a simple trick like constructing a sentence with the name in it and tokenizing this sentence can partially solve this problem. Such a sentence that would be grammatically correct and not semantically terrible could be something like “This is /name/”, but realistically, this sentence was quite likely not at all common in the training process of MorphoDiTa. Some foreign words can be erroneous as well and keeping their original form might be the only easy way around it.

Matching methods

Entity matching can be done with various degrees of sophistication. We provide a short overview of those degrees (1 – 4). 1 and 2 do not require any knowledge of the language they work with, 3 and 4 are language dependant. For simplicity, we will assume that we are only looking for mentions in one sentence at a time unless written otherwise. We also include an example of such matchings to demonstrate how successful we are likely to be.

1 String equality. Definitely the easiest method of entity matching. This method is based on a simple substring check which is later extended with ad-

značka
pro
překlad
v cap-
tion

Formátování
nadpisů

ditional functionality. In more detail, for each entity, we have multiple name variants and for each of those names, we check whether the name is a substring of the sentence.

We still need to work with letter cases. Named entities should have fixed letter cases and no additional processing is needed in most cases. In other cases, an established name for a named entity might be written with the lowercased first letter (Weasley family (Q716534) has Czech names 'Weasleyovi' /the Weasleys/ but also rodina Weasleyových /Weasley family/, but there are examples where those different names are completely different (Elizabeth II and Queen of England would be translated to Alžběta II. and královna Anglie). If we consider entities, that are commonly written with lower case (), the sentence now needs to be preprocessed so that for example the first letter is not capital. Moreover, there is no guarantee that common names will be lowercased in Wikidata. To conclude, nearly nothing can be assumed about the case of letters, and therefore one of the following solutions needs to be implemented: everything can be converted to one chosen letter case or some more sophisticated attempts at predicting, which words can have more version in terms of letter cases.

český

příklady
jako
škola,
tužka

Another problem that we may encounter is how to properly handle spaces. We will list some troublesome examples and accept the fact that not everything can be done perfectly. J. K. Rowling has J.K.Rownling as one of Wikidata names, confirming that both versions might appear in written text, but not all entities with similar name type have all space-variants listed in names. We assume that spacing around the '-' character might vary.

It is also not clear if word order in entity names is fixed (or at least almost always fixed). Even the simple reversion in name, that is sometimes used, will affect the performance of this method (J. K. Rowling and Rowling, J. K.). Even cases where the name is divided by for example apposition into two separate parts might exist.

The greatest weakness of this method is its inability to recognize entities if their name is inclined. To emphasize how many words are not in the same form as their lemma in Czech text, we colored them in the sample text. We elaborated on Czech language in CHAPTER XX, but just for simplicity - in English the verb to be has many different forms (am, are, were, was, would and so on), all nouns and verbs in Czech behave like this, quite often with many more forms.

vybarvit
a dát
link

link

2 String similarity (approximate string matching). String similarity is still based on simple string manipulation, no vocabulary or other language knowledge is necessary. The goal is to find entity mention, even if its name is a little altered in the sentence. This alternation can include all of the issues listed for the previous method - cases of letters, spacing, word order, and word forms, but even better, it might help in cases, that we did not anticipate.

There are many metrics describing string similarity. Some could cope better with word order issues, some with word forms, some with spacing. We will not test all of them for our usecase, but still find it useful to mention them since in other than the Czech language, some might work well.

Edit distance. First category of string similarity metric is based on edit distance:

Levenshtein distance is the minimum number of edits (additions, deletions, and substitutions of a character) to get from one string to the other. As a metric

the ratio of Levenshtein distance and of the sum of the lengths of the strings can be used. This metric, unsurprisingly, deals well with mentions that are close to the names when it comes to the amount of edits needed, so mentions differentiating in a word form, different spacing, or letter casing will could be considered a match.

Damerau–Levenshtein distance is very similar to the previous, but a transposition of two adjacent characters is considered an edit. We might argue that some Czech words tend to transpose the last characters in different word forms and thus this metric could work better for those forms, but there might be a higher risk of false positives.

One more thing to mention about edit distances is that they count the distance of two string, in our case of a name and of a substring of a sentence, because we do not expect an entire sentence to be entity mention. Therefore we need to decide on a logic for choosing substrings of a sentence to count the distance on, without diving too deep into this, the time complexity (even though both the sentence and the name length is relatively small) can be high if we consider the amount of data we need to process. (Let s, n be lengths of a sentence and a name, there are $s^2/2$ substrings and each edit distance can be computed in sn , leading to s^3n).

Token based. Another category is based on tokens. For those metrics, we can either use the tokenized sentences (by an actual tokenizer) and try to tokenize names, so that the format matches, or we can use naive tokenization like removing non-alphanumeric character and splitting on spaces.

The tokenization converts both the sentence string and the name string into a set of tokens (S, N respectively), so metrics that work with sets can be utilized: Intersection over union is computed as $|S \cap N|/|S \cup N|$. Any other set similarity measure can be used.

Token based metrics - due to their set nature - ignore the order of tokens and therefore could solve issues with mentions in which the word order is not the same as in the name. On the other side, an increase in false positives is to be expected and some additional postprocessing is needed to determine which token in the sentence should be considered a mention if the token was used in the sentence multiple times. We also feel obligated to mention that once again, we are not trying to find the similarity of a sentence and a name, but of a substring of a sentence and a name. This leads to the idea of removing all tokens, that are in a sentence and would worsen the metric and in result modifying the formula for intersection over union to $|S \cap N|/|N|$.

3 Sequence based. Just to be a bit more comprehensive we include another type of metrics - sequence based, even though we doubt that it is the best approach for entity matching. They ignore words as wholes and we do not see any advantage of those metrics for our use case.

Ratcliff-Obershelp similarity finds the longest common substring that is longer than some limit and recursively does so for the non-common parts of strings. The result is based on the ratio of (double the) length of common parts and overall length.

Bigram (or n-gram) intersection over union which converts both strings into a set of n-grams (n adjecant characters) and performs intersection over union. This time reducing a sentence into a substring is not that straight forward and would require additional attention.

Morphological analysis. Moving on from methods that are mostly unaware

of the language they work with, we will finally use the morphological analysis we mentioned earlier.

With lemmas of both the sentence and the name, we can use any metric from the previous subsection on string similarity (joining the lemmas on the space char if the metric expect only two input strings).

If we decide to keep the names in their original form (tokenization on them can be error prone, as we already explained), we can try to use the correct form of the tokens in the sentence. For each lemma, we get a set of all its possible forms - a lexeme, now we can modify the previous metrics to work with lexemes instead of tokens.

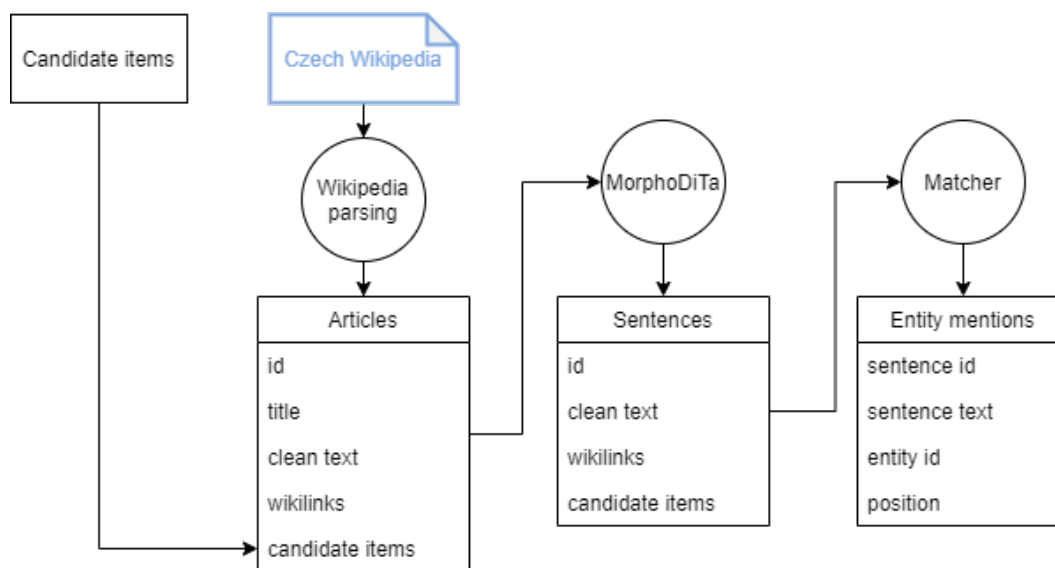


Figure 3.3: Matching with morphological analysis

4 Advanced concepts.

A proper entity matching (either in named entity recognition or entity linking) might be expected to recognize entity mention even if the entity is not mentioned explicitly by its name. Pronouns should be assigned an entity they represent (if they do) and other nouns as well. In languages like Czech where the subject of a sentence is often omitted the entity mention is even less obvious but still present. Since the topic of this thesis is not entity matching, we will not debate techniques to achieve this level of matching neither will we implement them.

Sfter looking at the results, we used a simple metric but we still find it useful to keep this summarization of different string metrics as part of this thesis. A detailed description of the matching method CERED was generated with is written in XX .

3.3.3 Wikilink Mentions

As we already mentioned, from our point of view Wikilinks are entity mentions created by Wikipedia editors. The text part of the link can in theory be anything providing us with some more advanced examples of entity linking, that our matching methods cannot perform.

V pátém díle McGonagallová říká, že předmět vyučuje již 39 let

We want to enable the users of CERED to distinguish relation mentions that were created based on two Wikilinks from all others. Since this data is not fully supervised and the word supervised is used often (semi-supervised, distant-supervised, etc.) we decided to call it **silver**, because they are not of the optimal quality that is usually labeled gold, but they are the best we can get.

přetíženo

3.3.4 Relation Matching

If a sentence contains two entity mentions that are related, chances are that the sentence in fact does express their relationship and thus is a relation mention. This concept is called **distant supervision assumption** and can be also formulated in the following way: If two entities participate in a relation, all sentences that mention these two entities express that relation. This assumption is commonly used, even though it is clearly not correct, because it is easy to use it. To tell how often this assumption is violated is labor-intensive, luckily research has been done on this topic. In the Riedel et al. [2010] the distant supervision assumption is compared to an **express-at-least-once assumption** which states that if two entities participate in a relation, at least one sentence that mentions these two entities might express that relation.

link

They sampled 600 relation mentions from two corpora, both created by distant supervision on Freebase (knowledge base commonly used before Wikidata took over) and two text corpora - Wikipedia articles and the New York Times corpus. These 600 samples represented three different relation types (nationality, place of birth, and contains) and were sampled so that there were 100 samples of each type in each corpus. We include their results in table XX They concluded that Wikipedia is a very specific type of text corpora, because articles are centered around entities. We believe that the reasoning can be extended with the fact, that freebase contained information from Wikipedia infoboxes, and those infoboxes were created based on the textual information.

table

For the authors the results signalized that a more sophisticated tool is needed instead of relying on the distant supervision assumption. We acknowledge that such a tool is needed but at the same time we believe that in our case, where we create CERED based on Wikipedia and Wikidata, the precision they estimated is sufficient. We also assume that Wikidata project is more suitable for this task than was Freebase.

We want to mention that we build CERED to easily fit into the modern deep learning models and to be as simple as possible. Therefore, the main piece of text we use is a sentence, it might seem intuitive, but it has one downfall. If the relationship extractor was to be used on a real text not to determine where some relations are mentioned but to provide a summary of relations expressed by the text as a whole, some information will be lost.

najít
článek
nebo
někam
přesunout?

3.3.5 Relation Inventory

In chapter XX some examples of Relationship classification datasets were introduced. The creators of those datasets claim that in the creation process they first decided on the relation inventory (relation types). Creating the relation inven-

tory seems to be the straight forward and rational approach and we wanted to create such inventory before actually implementing the CERED generator. We stumbled upon the following issues.

Issue 1. Wikidata relation inventory (properties in Wikidata terminology) is an order of magnitude larger compared to the traditional relationship extraction datasets and handpicking our inventory is overwhelming. We even considered reducing the size of this inventory by creating our own relations that would combine Wikidata relations (parent would be the combination of mother and father relations).

By restricting the Wikidata inventory to just some properties we reduce the size of CERED and if we choose the inventory without considering the number of mentions per relationship, the best-represented relations could be omitted.

Issue 2. Knowledge bases, in general, do not contain negative relations (such relations that could be easily mapped to the “no relation” or “other relation”), but for relationship extraction negative mentions are essential. If we generate mentions using all properties we can later decide which relationships will be in the inventory and the rest of them relabel to “other relation”. If we were to assign all tuples of entity mentions that share a sentence and are not related as “no_relationship”, we could increase the noise in CERED because not all relationships are in Wikidata and therefore part of the no_relationship mentions could in fact be a positive mention. The commonly used ratio of negative and positive mentions is .

While curating the inventory, we should keep in mind that we are not just choosing the relations but also their representations and we need to attempt to fulfill the three following requirements to the best of our abilities:

- Each relation needs to be represented enough.
- The more balanced relation representation sizes the better.
- There should be enough negative mentions and their negativity should be assured.

3.3.6 Result Evaluation

The most challenging aspect of working with Czech Wikipedia and Wikidata is their size and diversity. To the best of our knowledge there is no strictly followed guideline when it comes to editing either the articles or item information. Just converting Wikipedia dump to clean text will be challenging due to user defined templates and other constructs we might be unaware of. On the other side names in Wikidata can be too general (like someone’s first name) and create false entity mentions.

We prepared several metrics and methods to measure the quality of the implemented generator and we will list them in the table 3.4. Unfortunately going through the article and seeing what did and did not get recognized as a mention is still the most powerful method, therefore we decided to develop a simple app that can prettify the output of the generator and makes the process of looking at the results less painful.

- FA The overall count of found mentions - to some extent the greater the better - at least in the beginning with naive matching methods. With more sophisticated matching, this number should increase. On the other side, this measure will decrease with more higher precision.
- FA If the distribution of the amount of found mentions (both the entity mentions before relation matching and the relation mentions) over some domain is peculiar (contains abnormalities such unexpected peaks) the quality of not only those mentions might be lower. The domain can be anything from the following or even multiple of them at the same time: sentence, article, relation, entity, sentence number (the order of the sentence in an article), entity pair.
- NA Checking the anomalies detected by the previous methods.
- NA Checking an article and realizing what did and did not get matched.
- FA Some articles could be labeled by hand and test could be created.

Figure 3.4: Quality evaluation methods and the potential for automatization (Fully Automatic, Not-Automatic)

Viewer

The purpose of this viewer is to present the results in a more graphical way to fasten and pleasant the process of checking them, which will be done often and will take a significant amount of time.

We want the viewer to be able to show the statistics about the generated data, that were collected during the generation, the configuration that was used to generate the dataset, and mainly to show an article with the found mentions (entity and relation).

Streamlit made implementing such viewer quite easy and we used spaCy's visualizations.

<https://www.aclweb.org/anthology/P19-1074.pdf>

3.4 Used technologies

We chose Python to be our main programming language. To be able to work faster with a bigger volume of data, we wanted to use a CPU cluster, which leads to Spark. To top it, we will use MorphoDiTa to work with the Czech language. We implemented a simple Streamlit app we used to comfortably view the results of our Spark queries.

In this section we will briefly introduce these technologies. **Neřešit moc do detailu, cca dva odstavce o každém.**

3.4.1 Python

Python is probably the most popular programming language in the ML community. It is a high-level language with a wide range of libraries. Libraries as

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spark
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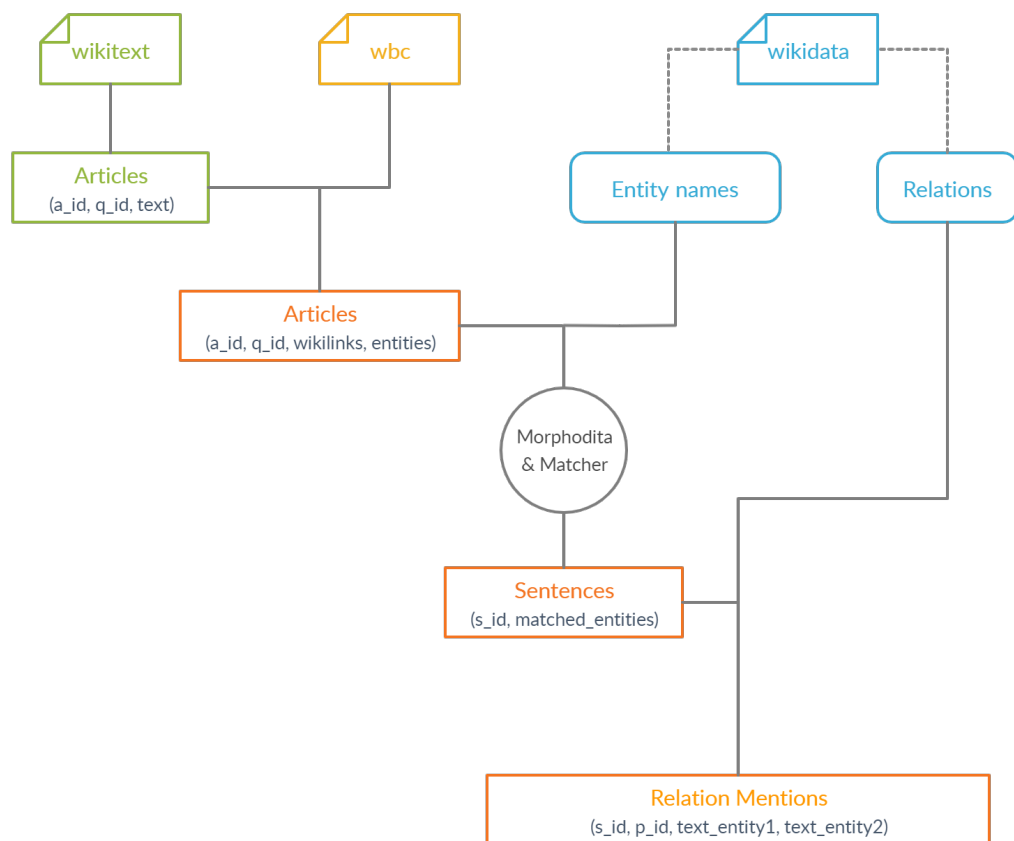


Figure 3.5: Zjednodušený diagram výroby korpusu

NumPy, Pandas and Spark enable fast and accesible computation. Tensorflow, scikit and PyTorch allow users to focus mostly on data and ideas in machine learning. Less known libraries help us with Wikipedia parsing (wikitextparser, mwparserfromhell) or easy-to-create web apps (streamlit).

3.4.2 Spark

Apache Spark framework provides query like API and runs on clusters. This way parallel computation can be implemented without actually implementing any parallelism. Therefore, Spark can boost the speed of computation as well as the available memory for the computation.

3.4.3 MorphoDiTa

MorphoDiTa Straková et al. [2014] (Morphological Dictionary and Tagger) is an open-source tool for morphological analysis of natural language texts. It is designed to work well on inflective languages and achieves state-of-the-art results for the Czech language. MorphoDiTa has a python package via which we can do all standard operation such as tokenization (splitting text into sentences and words) and lemmatization (disambiguation of the inflected form of a word).

3.4.4 Streamlit

Streamlit is a framework for creating simple web apps. It has minimal and practical API designed for users from the data science / machine learning community. We use this library to create a more pleseant way of viewing the generated dataset.

typografie

3.5 Implementation

3.5.1 Wikidata preprocessing

This module aims to load the wikidata dump file and output three lists. The first list contains QPQ triples, triples of ids representing a relationship (Q173998 P3373 Q187923 for example). The second list provides us with names for the ids mentioned in the first list (Q187923 Ginny Weasley, P3373 sibling). The third one provides the mapping of entity id to the title of the corresponding article if such exists (příklad). Those three lists will serve as the source of structured data, as we discussed in XX.

The first step of our preprocessing is to filter wikidata to remove entities, that we will not use. We require each entity to have at least one Czech name (alias or label), otherwise, there would be no good way to find mentions of that entity later in the entity matching step. CERED creation does not require the Czech names of relations so we will keep all of them.

Apart from the filtering, we should consider whether we might benefit from keeping more information about a relationship (meaning the instantiation of a relation) than just the ids. Wikidata relationships often contain additional information specific for the relation type. For example, some relationships are valid only for some period of time. The minister of magic changes every few years

(“position held” relationship between Cornelius Fudge and the Ministry of Magic has following additional information attached to it: start time 1990, end time 1996, replaces Millicent Bagnold, replaced by Rufus Scrimgeour). In our use case, as we plan to limit text analysis to the syntactic level, such information is not beneficial.

The second step addresses removing duplicate relationships that differ only in the additional information tied to the relationship (CBS received many Peabody Awards for example). Such duplicates where the entire QPQ is the same would not be useful in the future and might require special attention in the relation matching step. We will remove even relationships that differ only in the “P” part. If we kept them, in the relation matching we would either create multiple relation mentions (sentence with two tagged entities and the label of their relationship) that only differ in the relationship. CERED is supposed to be a dataset on which it is possible to train a model in a single label classification task. Such mentions would result in the same inputs (sentence with two tagged entities) and different outputs (the relationship label). We could change the format of our dataset to have a set of relations for each mention, but such data is confusing, non-traditional and overall not what we aim for in this thesis.

After these steps, the first list contains approximately 2 million QPQ triples.

3.5.2 Wikitext parsing

This module aims to parse wikitext (Wikipedia markup language) from the Czech Wikipedia dump into a clean text with attached information about wikilinks in the original markup.

As we already explained in XX, wikitext contains a lot more than fully unstructured data. Different kinds of infoboxes, tables or lists are contained within the sentence-like text. Some of these elements are implemented using the so-called template syntax. Therefore, it would be tempting to simply remove all the text that is contained in a template. The problem is that not all templates are bad. For example, we may use a template to divide the text into two columns containing valid sentences. Therefore, discarding all such data seems unnecessarily harsh.

When developing the methodology for wikitext parsing, there was not a “gold” to compare it with. The only means of evaluation we had at the time was repeatedly going through a small set of articles and trying to discard unnecessary data. We tailored the rules for wikitext parsing to these articles in such a way that only sentence-like parts remained.

Once we implemented the whole CERED generator and were able to see the relation mentions, we realized that the previous method of evaluation was not good enough. Therefore, we adopted a new one, as described in XX (). We looked at the different histograms and investigated the abnormalities. For example, a lot of sports articles report results of a match (tournament, event?) and these are often stored in custom tables that were not filtered by the rules from the previous paragraph. Moreover, these tables oftentimes contain information about the nationality of the players, resulting in a huge amount of matched entities and relations.

Based on the analysis of all the available data, we decided not to include the

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following content in the clean text: HTML tags within wikitext headings tables lists templates matching the following patterns: `obsazení*`, `sloupce*`, `seznam*`, `příbuzenstvo*`, `*předkové*`, `*box*`, `*locmap*`, `*tabulka*`. wikilinks to categories and files

One more technical issue we encountered was correctly assigning spans to wikilinks, i.e. where the link starts and ends in the text. We can demonstrate the problem on the following sentence: “The main [[story arc]] concerns Harry’s struggle against [[Lord Voldemort]], a dark wizard who intends to become immortal, overthrow the wizard governing body known as the [[Ministry of Magic]] and subjugate all wizards and [[Muggle]]s (non-magical people).” The correct span for Muggles should contain the trailing s even though it is not part of the wikilink itself. In Czech such trailing characters are common. The set of chars that seem to end wikilinks written in such forms are ‘ , . n’.

One more thing we mentioned in the analysis about wikitext is the possible boost of performance if the text-part of a wikilink was added to the set of names for the given entity. We exported such names, kept only those that were not already added to wikidata, and read through many of them. This process is time-consuming because one often has to actually look up the entity to know whether a given name is sensible. Even though we do not have any data about the proportion of good and bad names, the overall impression was clearly leaning towards not using such data. The two main reasons were that commonly the name was actually a class name, not instance name (like school linking to Hogwarts). Cases, where the name was just a pronoun, were less frequent but would likely cause much trouble later on. (napsat, že čeština umí zájmena úpužívat fakt mistrně a všude? nebo to napsat do části o češtiny a tady odkaz?)

data pro to, jak (ne) užitečné jsou texty linků jako dodatečná jména data nejsou

3.5.3 Entity matching

We discussed in great detail the pros and cons of different entity matching methods, implying that the more complex the matching method, the better. We work with a single language and tools for lexical analysis are available and reliable. Therefore implementing language-independent matching methods (string similarity for example) is not beneficial.

We load the entity names in a slightly transformed form. We lower the case and add spaces around every dot character. We used lexical analyzer to split text to sentences and to obtain features from sentences (tokens, lemmas and lexemes). An entity name (sequence of k strings-tokens separated by a space) is matched in a sentence if there is a sequence of k consecutive tokens in the sentence such that each token in the name is a member of the lexeme of the corresponding token in the sentence.

We intended to allow a less strict word order, but we were unable to justify such a choice. After reading several articles we did not find any entity mentions that would be newly matched. This might imply that even though word order is relatively free in Czech, noun phrases tend to keep their word order. The other explanation is based more on the fact that a human reader is more likely

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to recognize entity mention if it is in the standard word order. Looking for entity mention is again more time consuming than it seems, because we do not know, what is a wikidata entity, therefore a lot of looking up is involved and we believe that often we would not have thought that something is a wikidata entity even though it is. Such "improvement" could still raise the number of entities matched but probably would lower the precision.

We considered allowing one special case. Most articles are based on one entity, therefore we expect many sentences to mention this entity. Often the entity is mentioned either by a pronounce (pronounces that express the subject are typically omitted in Czech), or by part of its full name. Přijali ho do školy čar a kouzel v Bradavicích. Když se Harry vydal do Bradavic, našel nového kamaráda Rona Weasleyho. .. Pak už jel "domů" a musel přežít další dva měsíce u Dursleyových. We already stated that we will not attempt to deal with pronounces. We tried to propose rules for choosing the correct substring of the entity name. The diversity of wikidata makes such a task extremely difficult. Together with the risk that we would decrease the precision of entity matching we decided to stick with full names only.

In the wikitext parsing section, we prepared spans and ids for wikilinks. We merge these with the ones matched by this module and post-process them. We discard each mention whose span is within a span of different mention of the same entity. This removes duplicates and keeps the one that is more specific.

jestli bude čas, tak udělat statistiky i pro jiné metody
na obrázku s volemtorem ukázat, jak to nakonec funguje

3.5.4 Relation matching

So far we obtained sentences with tagged entity mentions. For each tuple of entity mentions within the same sentence, we checked if a relationship of those two entities was present in wikidata (using the prepared QPQ list). Given the filtering in wikidata preprocessing we are guaranteed that there is at most one such relationship.

At this stage, we need to address likely incorrectly matched entities that make the dataset bloat. One example of such bloating that we encountered was in an article about kindergarten , in the sentence Jsou závazná pro předškolní vzdělávání v mateřských školách, v mateřských školách zřízených podle § 16 odst. 9 školského zákona, v lesních mateřských školách a v přípravných třídách základních škol. thousands of relation mentions were found. Many kindergartens are named Marešská škola (kindergarten), all of them are an instance of the abstract kindergarten entity and therefore candidate entities. If a sentence contains the term "mateřská škola" (or its form), all these entities will be matched. And the relationship "Mateřská škola is a mateřská škola" will be assigned many times as well.

After investigating many other unusual cases, we decided to discard any sentence with at least 10 entity mentions in it. We also tried to experiment with different limits, but the results were unconvincing. For example, increasing the constant to 50 keeps an additional 13% of relationship mentions but extends the set of sentences only by 1%.

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na
<https://cs.wikipedia.org>

3.5.5 statistiky jak to dopadlo

The full CERED dataset, which was obtained by the process we described in the previous sections, contains almost one and a half million relation mentions. In the next few paragraphs, we will talk about some more detailed statistic of CERED. And we will propose a few other CERED versions.

The mentions are from 293591 articles (=293591 přispělo aspoň jedním), on average slightly less than 5 mentions are from the same article with the median of nearly 7. The article with most mentions is Spojené království (United Kingdom).

There are 490501 different sentences that are used in the mentions. We set the limit on entity mentions per sentence to 10. On average there were approximately 3 relation mentions in a sentence (that had at least one mention) and the maximum of 72 mentions per sentence was reached 34 times. The length of sentences ranges from 2 to 401 tokens, the very short ones usually came from templates that were not removed, on the other hand, the very long ones are often caused by incorrectly written articles. We tried to remove all templates to see if the range (and distribution) of the number of words improves, but we did not find a significant improvement.

Another possibility is to observe how the position of a sentence in an article influences the number of relation mentions. We expected that the first sentences in an article will contain the highest number of relation mentions. The first sentences tend to contain wikilinks and the use of pronouns or shorter names is limited because each entity has to first be introduced by its full name. As we can see in Figure XX, our hypothesis seems to be correct. 904803 mentions come from sentences that are first in their respective articles. This constitutes over 60

3.5.6 CERED Versions

The full CERED is already a valid relationship classification dataset. It has nearly one and a half million mentions, but as we discussed in the previous section, some of them might be of poorer quality than others. In this section, we will describe different versions of CERED with CERED0 being the biggest (least filtered) and CERED4 the smallest.

Each version is split up into three disjunct sets: train set, dev set and test set. Ideally, the test set would operate on a different set of entities (so that models learn to predict relationships based on sentences, not on the knowledge of entities). We believe that such a restriction is unnecessarily strong. Some entities are mentioned in many articles, which does, in fact, make them part of common knowledge (connected to the language we train on). Instead, we decided to relax the restriction to distinct articles. We sampled two sets of 10000 articles, one for test and one for dev set. In each version of CERED, the same articles are used for dev, test and train.

CERED0

CERED0 is the raw dataset just as we described it in the previous section. We do not artificially change the relation type, so no negative relation is present. We do not recommend this version for direct training, we mostly keep it to preserve the full information obtainable from our generator.

CERED1

CERED1 is close in size to CERED0. We removed long (over 100 words) and short (under 5 words) sentences. We also changed labels of underrepresented relations to “other relation”, which will be the negative relation in CERED1.

CERED2

So far, one sentence could be included multiple times in a dataset. Moreover, there was no required number of mentions per relation, for the relation to be considered a valid relation. And lastly, we did not try to handicap overly represented relations. In CERED2 we start with CERED1, we discard relations (and their mentions) that were not represented enough (under 100 mentions). Then, if a sentence was used in multiple mentions, we choose the mention of the least common relation in the sentence and we discard the others.

CERED3

Even after the restriction on the uniqueness of sentences, half of the CERED2 sentences are the first sentences within the articles they originated from. Such sentences have a rather unique structure that is not as common outside of Wikipedia. This inspired CERED3 which is the remainder of CERED2 after removing all mentions in “first” sentences.

CERED4

There are two stages in the CERED generation process that might be relatively unprecise. The entity matching stage and the relation matching stage. CERED4 keeps only the relation mentions from CERED3, in which both entities were manually-labelled directly in wikitext in the form of wikilinks. The CERED4 dataset is, therefore, the smallest, but has the highest potential to be precise.

3.5.7 •

Even though this is not exactly part of wikidata preprocessing we will o tom, že named entity jsou instance, že stačí jít po cestě instance-podtřída*. Že je těžké vybrat rozumné věci jako “rodiče”, že mezi nepříjemnými entitami jsou třeba seznamy, kategorie a podobně, že ve finále to hlavní jméno je velké právě když je to instance.

někam zmínit, že test data jsou ze spešl článků

3.6 Results

statistiky výsledného datasetu, ve kterém jsou zanechány všechny třídy + jedna “deploy” verze, ve které jsou i negative mentions

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Part II

Training

4. Previous Work on Relationship Extraction

In this chapter, we first introduce the most popular pre-trained models that are currently used in NLP. Then we discuss different metrics that are used on Relationship Extraction. Lastly, we research previous work done on the topic of training models for the relationship extraction task.

4.1 Pre-trained Models

Lately, NLP tasks are dominated by solutions using pre-trained deep neural models. In this section, we introduce BERT, the first well-known model of this type that has set the trend. **BERT, albert? + obecně asi transformer architektura**

4.1.1 BERT

4.2 Metrics

This section focuses on metrics in the Relationship extraction task, we first define those metrics and later discuss the pros and cons of each.

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4.2.1 Binary classification

Let us start with metrics for binary classification. In binary classification, we are presented with an input vector and the goal is to determine whether the vector is of class A or class B. Each prediction then falls into one of the following categories: correctly classified A input, correctly classified B input, wrongly classified A input as B, and a B input wrongly classified as A (Figure 4.1).

		Predicted class	
		Positive	Negative
Actual class	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

		Predicted class	
		A	B
Actual class	A	True A	False B
	B	False A	True B

Figure 4.1: Confusion matrix for binary classification

Another way to look at the same situation is to just predict whether an input is of class A or not. Those that way the prediction is a True / False value determining whether the model is of class A. This way, we can define the previously

mentioned categories without using the specific classes as **true positive** (TP), **true negative** (TN), **false negative** (FN) and **false positive** (FP). Visualization of the result of classification on a dataset is called a **confusion matrix**, we include such matrix 4.1). We will use the abbreviations to represent the number of predictions that belong to the given category.

Accuracy expresses the ration between correct and incorrect predictions.

$$Acc = \frac{TP + TN}{FP + FN} \quad (4.1)$$

Precision expresses the ratio correctly predicted positives within all predicted positives. Therefore, precision is a good metric if we want to avoid mistakenly classify falses as positives.

$$Prec = \frac{TP}{TP + FP} \quad (4.2)$$

Recall is the complementary metric to precision. It expresses the ratio of all positives that were correctly predicted. In other words, it should be used when we need to find the maximum of positives in the data.

$$Rec = \frac{TP}{TP + FN} \quad (4.3)$$

Let us show three use cases, each of the defined metrics will be the best fit in one case.

Suppose we have a collection of pictures of cats and dogs for adoption. If we were to classify pictures of cats and dogs based on the animal, we would most likely want to maximize the number of correct predictions. Accuracy would aim exactly for that.

If we knew that some adopters suffer from cynophobia (fear of dogs), suddenly the classifier should accommodate the fact by optimizing precision (where a cat is a positive). Note that precision (and recall) in binary classification will return different values if we swap which class is the positive and which is negative.

If the demand for cats extends supply and therefore we have more dogs than cats in the collection, searching for cats could get harder. In such a case, we would want to make sure that all cats are actually classified as cats, and recall would help with that.

To emphasize that the right choice of metric is significant suppose that we have balanced data (both true and false classes are equally represented). If our classifier just predicted that every input is positive, we would obtain the following: 0.5 accuracy, 0.5 precision, and 1 recall. If we were to predict all negatives accuracy and precision would remain 0.5 but recall suddenly drops to 0. If we were to randomly predict the result with even chances for both classes the expected results are 0.5 for all of those metrics. We just described three very different classifiers and the only thing we learned from accuracy and precision was that they were equally bad, without any insight about them. Recall in contrast successfully gave us insight about what the predictions likely are, but evaluated a bad classifier with the highest possible score.

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This whole section is in this thesis mostly to remind us that if we want to score well in a given metric, we will likely exploit the metric even if it might actually worsen our classifier. The choice of a metric for a task determines what gets optimized. Later in this section, we will debate such issues in our case, in the relationship extraction task.

F1

Often we might want a trade-off between being as precise as possible and recalling as much as possible. **F1 score** is a harmonic mean of precision and recall (scaled to range from 0 to 1):

$$F1 = 2 \frac{PrecRec}{Prec + Rec} \quad (4.4)$$

and is quite widely used in competition tasks.

4.2.2 Multiclass classification

We already run into issues with asymmetry of precision and recall in binary classification (it is dependent on which class is chosen to be the positive one). We can address this by creating metrics per class. In the previous example about binary pet classification, we would get two sets of metrics, each describing the ability of the classifier to recognize given class apart from the rest.

Now we can easily extend this per class approach to multiclass classification. The formulas will remain exactly the same, only the way we obtain the TP, FP, TN, and FN values is a little different. In a sense nothing changed - if we imagine that the classifier is still binary then the situation is exactly the same. But if we compute those values out of confusion matrix (for class B) then TP is the value on position [B, B], FP is the sum of all in column B without TP, FN the sum of the row B without TP and the sum of cells outside of the Bth row and column are the TN. (Figure 4.2)

		Predicted class		
		A	B	N
Actual class	A	True A	False B	False N
	B	False A	True B	False N
	N	False A	False B	True N

Figure 4.2: Confusion matrix for N-class classification

As a solid way of examining the quality of the classifier, one could simply look at the confusion matrix and at all the per-class metrics. Although this would be insightful, it is not the most practical in terms of a clear comparison of two classifiers. Ideally, we aim for a metric or metrics that are as descriptive and comprehensive as possible but define an ordering of the classifiers.

Intuitively we will minimize the number of metrics by combining them into one value. To do so, we should acknowledge that the dataset we evaluate the performance of a classifier and a metric on needs to be taken into consideration.

An ideal dataset would be perfectly balanced. In real life we encounter two types of imbalance in datasets:

class representation distribution (CRD) is not uniform - classes are not equally represented
class representation distribution is different in the test and the train part of the dataset

The second imbalance is tricky. Often, when optimizing the classifier, we do not know the CRD of the test dataset. We will therefore mostly focus on the first one.

Macro-averaged metrics

The first method that comes to mind when we aim to combine the same metric of multiple classes into one, is the arithmetic mean. In most libraries and papers the term macro-[metric] (macro-recall, macro-F1, etc.) is used. Macro averaged metrics tend to be the easy option that is used without much thought. So much so, that even though two macro-F1s are being used, often the exact formula is not included in papers. (The more common formula is the arithmetic mean of classes F1s, but the less often formula where the F1 is computed from macro-recall and macro-precision is also used Opitz and Burst [2019].)

Weight-averaged metrics

If we aimed to pretty much just maximize a metric ignoring the class, instead of averaging the classes with the same weight, we would weight them by their support.

co je support
vzorec

4.2.3 Relationship extraction metrics

Whether or not to use macro metrics depends deeply on the use case and the dataset. In our case, the datasets tend to be very imbalanced (the majority of data are negative mentions, and even within the positive mentions the classes are highly unbalanced). This often leads to the idea of computing the combined metric only from positive classes.

přehled co se běžně uvádí u kterého datasetu
problémy s tím, že CERED je sice taky nevyvážený, ale dost jinak

4.3 Relationship Extraction Models

matching the blanks
další články

Conclusion

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A. Attachments

A.1 First Attachment