Universität
Zürich[UZH]

Bachelor's thesis
presented to the Faculty of Arts and Social Sciences
of the University of Zurich
for the degree of **Bachelor of Arts UZH**

Toward automatic diagnosis of medical conditions involving speech impairment

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Submission date: June 1, 2021

Abstract

Up to now, few studies have explored speech impairments and their computer-assisted analysis in German. This thesis introduces a pipeline of automatic transcription and manual annotation of German speech data. The pipeline's purpose is to collect data from impaired speakers in order to apply computational linguistic methods for analysis. These methods provide the opportunity to assist in the detection of medical conditions, which include speech or language anomalies. The annotated data can be used to train machine learning algorithms, which presents a promising approach towards the automatic detection of speech impairment.

Zusammenfassung

Bisher gibt es nur wenige Studien, die sich mit Sprachstörungen und deren computerunterstützten Analyse im Deutschen befassen. Diese Arbeit stellt eine Pipeline für die automatische Transkription und manuelle Annotation Deutscher Sprachdaten vor. Der Zweck der Pipeline besteht darin, Daten von beeinträchtigten Sprechenden zu sammeln, um computerlinguistische Methoden für ihre Analyse anzuwenden. Diese Methoden bieten die Möglichkeit, die Erkennung von Krankheiten, die Sprachanomalien mit sich bringen, zu unterstützen. Die annotierten Daten können zum Trainieren von Algorithmen maschinellen Lernens verwendet werden, was einen aussichtsreichen Ansatz für die automatische Erkennung von Sprachbeeinträchtigungen darstellt.

Acknowledgements

First and foremost, I would like to thank my supervisor Dr. Sarah Ebling for her contagious enthusiasm for the subject of this thesis, sympathetic ear, and her meaningful suggestions which advanced my work. I would also like to thank Susanne Kempe for her contribution from the perspective of a speech-language pathologist and her inputs concerning vital future work. I am also grateful to my family and friends for their great interest in this thesis, and Domenica Polimeni for proofreading it.

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Acronyms

AD	Alzheimer's disease
ASD	Autism spectrum disorder
ASR	Automatic speech recognition
DLD	Developmental language disorder
HC	Healthy controls
MATTR	Moving-average type-token ratio
MCI	Mild cognitive impairment
ML	Machine learning
NLP	Natural language processing
NN	Neural network
RSB	Reciprocal social behavior
TD	Typically developing
Tf-idf	Term frequency–inverse document frequency
TTR	Type-token ratio
WER	Word error rate

1 Introduction

Early diagnosis is crucial for the effective treatment of any disorder or disease. In both neurodevelopmental disorders such as autism spectrum disorder and developmental language disorder as well as neurodegenerative diseases such as Alzheimer's disease, which are currently incurable, adequate education and therapy can help with the support of children and slowing down the decline of cognitive function of the elderly, respectively. Symptoms of these diseases often include speech or language impairment. There is experimental evidence in the literature that speech impairment is one of the earliest indicators of the aforesaid diseases, and some researchers suggest that language anomalies appear even years before a diagnosis is made [Ahmed et al., 2013]. Some language peculiarities are very subtle, and therefore, are not detectable by using standardized tests. Computer-aided analysis of natural speech can greatly improve diagnosis by quantifying certain language characteristics. In comparison to standardized tests, speech data can be collected easily in relatively natural settings and noninvasive ways, and it is possible to investigate the progression over potentially long periods of time [Fraser et al., 2014].

Computational linguistic methods provide an opportunity to automate and thereby expedite the analysis of speech data. Of course, computational linguists would never replace doctors, but computer-assisted diagnosis can help to preselect potential patients in order to provide the best possible treatment. Such a preselection could also relieve the health system and allow the screening of many individuals (for example, large parts of the elderly population in order to prevent dementia), which is too expensive to be done with clinical tests [Lehr et al., 2012].

Chapter 2 provides an overview of the linguistic features of speech and language impairment in three different clinical conditions: developmental language disorder, dementia, and autism spectrum disorder.

Large parts of the research on speech and language impairment as well as experiments using computational methods including machine learning have been conducted with English data (see Chapter 3). Most features appear to be language independent, but studies in other languages are important to develop an understanding of speech and language impairment in a more universal manner. Language-specific data will be indispensable to train machine learning models for automatic diagnosis, which has been done almost exclusively in English so far.

Therefore, within the framework of this thesis, a platform prototype was developed and is presented in Chapter 4. This platform automatically transcribes German speech samples and serves as an annotation interface in order to collect annotated speech data for future experiments on machine-learning-driven diagnosis in German.

Finally, Chapter 5 provides a summary of this thesis and outlines the next steps to advance the automatic diagnosis of cognitive diseases based on German speech data.

2 Speech and language disorders and their characteristics

The ways in which the language of individuals with different medical conditions deviates from healthy individuals have been studied extensively. This chapter gives an overview of the mostly language-independent features of speech observed in developmental language disorder, dementia, and autism spectrum disorder that have been reported in the literature.

2.1 Developmental language disorder

Developmental language disorder (DLD), formerly known as specific language impairment, denotes the condition of children having delayed or disordered language development in the absence of a diagnosis of autism or any other neurological or hearing deficits that would explain the condition [Solorio, 2013; Leonard, 2014; Schöler and Welling, 2007]. Children with DLD also show a normal IQ and no problems with oral motor skills. It is controversial that, despite its exclusionary definition, children with DLD are more likely to have problems with memory, attention, mathematics, and problem solving, or to exhibit reading and writing disabilities [Schwartz, 2017; Schöler and Welling, 2007]. Tomblin et al. [1997] found that over 7% of more than 7000 examined American kindergarten children have DLD. The diagnosis is important because DLD can negatively affect social development and cause poor performance in educational settings [Clegg et al., 2005; Law et al., 2009]. Even though the literature suggests that language deficits will persist [Law et al., 2009; Johnson et al., 1999; Law et al., 2000; Rescorla, 2009], early speech therapy is crucial to reduce the extent of the symptoms [Gabani et al., 2011]. For monolingual English-speaking children, there are norm-referenced tests to detect language deficits such as the past tense [Marchman et al., 1999] or the third person singular task [Simkin and Conti-Ramsden, 2001], which classify children whose score is more than 1.25 standard deviations below the mean of the reference population in at least two of those tests as potentially having DLD [Tomblin et al., 1997]. Campbell et al. [1997] showed that such tests are negatively impacted for children coming from underrepresented populations. As an alternative to norm-referenced tests, processing-dependent measures such as nonword repetition [Campbell et al., 1997; Dollaghan and Campbell, 1998; Bishop et al., 1996] are an attempt to eliminate this bias. Another nonlanguage-specific test is to measure a child's ability to learn new information [Peña and Iglesias, 1992; Peña et al., 2001; Lidz and Peña, 1996]. However, a poor performance on these tests is not an exclusive indicator of DLD but of other learning disabilities [Kjelgaard and Tager-Flusberg, 2001]. Because of the disadvantages of standardized tests, an analysis of spontaneous speech is a very valuable approach [Botting, 2002; Redmond, 2004].

The most sensitive feature of DLD in English is the measure of finite verb morphology with an accuracy of 97%. Children with DLD show difficulty with clitics of finite verbs such as *-s* for third-person singular agreement or *-ed* for past simple in English [Schwartz, 2017; Gabani et al., 2011] and additional declination errors in Spanish [Jacobson and Schwartz, 2002; Restrepo and Gutierrez-Clellen, 2001; Bedore and Leonard, 2005]. Rice et al. [1995] also reported that functional morphemes are often omitted in DLD, but never used incorrectly when they are present. The reduced and incorrect use of grammatical morphemes such as suffixes, as well as function words such as determiners and prepositions, has been described as a feature of German-speaking children with DLD [Schöler and Welling, 2007].

Syntactic deficits begin with the onset of syntactic comprehension and production when DLD children exhibit a delayed growth in syntactic complexity [Schwartz, 2017]. Difficulty producing and comprehending syntactically complex sentences, for example those involving long-distance dependencies, seems to be universal, as it has been found in English-speaking [Deevy and Leonard, 2004; Marinis and van der Lely, 2007; Schuele and Tolbert, 2001], Swedish-speaking [Hansson and Nettelbladt, 2006; Håkansson and Hansson, 2000], Greek-speaking [Stavrakaki, 2006], and Hebrew-speaking [Friedmann and Novogrodsky, 2004, 2007; Novogrodsky and Friedmann, 2006] children with DLD. Schuele and Tolbert [2001] found that English-speaking children with DLD often omit obligatory relative markers in subject relative clauses. A syntactic feature of DLD language that is specific to German is the incorrect placement of verbs at the end of a sentence in main clauses [Schöler and Welling, 2007]. This is a typical mistake of all children acquiring German as a first language, but it persists longer in children with DLD.

In general, children with DLD start to produce and comprehend language later than typically developing children, their vocabulary remains limited [Schwartz, 2017; Clarke and Leonard, 1996; Dannenbauer, 2001], and they produce overall shorter utterances [Schöler and Welling, 2007]. They appear to struggle with verbs the most, especially those encoding mental states such as *know* or *think* [Johnston et al., 2001]. Schöler and Welling [2007] describe a decreased use of verbs and adjectives compared to nouns in German-speaking children with DLD. Some children with DLD also exhibit word-finding difficulties [Dockrell and Messer, 2007; German and Newman, 2004; Lahey and Edwards, 1999; Leonard et al., 1983; McGregor et al., 2002; Seiger-Gardner and Schwartz, 2008].

Besides morphosyntactic errors and reduced vocabulary and syntactic complexity, children with DLD also show pragmatic deficits producing narratives that are less cohesive and informative [Botting, 2002; Liles, 1993; Reilly et al., 2004; Norbury and Bishop, 2003].

2.2 Dementia

Dementia is the clinical symptom of deteriorating memory and other cognitive functions, which can originate from various diseases [American Psychiatric Association, 2013]. The most common cause is Alzheimer's disease, accounting for around two-thirds of dementia cases [Wankerl et al., 2017; Geldmacher and Whitehouse, 1996].

2.2.1 Alzheimer's disease

Alzheimer's disease (AD) is classified as a neurodegenerative disease involving decline in cognitive abilities with disease progression [American Psychiatric Association, 2013]. AD's most characteristic symptom is memory impairment due to damage in the medial temporal lobe[1] [Fraser et al., 2016]. When Alois Alzheimer first described a type of dementia in 1907, which later became known as Alzheimer's disease, he reported speech impairmentfs including paraphasias and halting speech alongside comprehension difficulties [Alzheimer, 1907]. In more recent literature, language impairment is mentioned as a secondary cognitive symptom of AD, but because the onset of abnormal speech may emerge in the early stages of AD [Ortiz and Bertolucci, 2005; Ross et al., 1990], it is an important clinical clue to diagnose AD in the first place. A definite diagnosis of AD can only be made in a postmortem autopsy of the brain tissue [McKhann et al., 1984, 2011; van de Pol et al., 2005], which demonstrates the need for reliable surface-level indicators.

[1] The temporal lobe in the brain is involved in processing sensory input into derived meanings for the appropriate retention of visual memory, language comprehension, and emotion association.

In a study conducted by Appell et al. [1982], all subjects diagnosed with AD had aphasia, suggesting that language impairment is a universal feature of AD, driven by impairments in episodic memory [Lambon Ralph et al., 2003]. Various studies have found that changes in language and speech may appear before a diagnosis: In a retrospective speech analysis, Ahmed et al. [2013] found that two-thirds of the elderly participants showed changes in connected speech production up to a year before their diagnosis of AD. Prospective cohort studies of ageing populations [Forbes-McKay and Venneri, 2005; Oulhaj et al., 2009] have also shown that language changes occur in AD patients years or even decades before their partners or families recognize cognitive deterioration [Ahmed et al., 2013].

The severity of language impairment depends on the stage of AD: Faber-Langendoen et al. [1988] found that 36% of mild AD patients and all of the severe AD patients investigated had aphasia.

[Appell et al., 1982, p. 74] described the language of AD patients as "verbose and circuitous running on with a semblance of fluency, yet incomplete and lacking coherence." The latter was also reported in studies conducting interview tasks and manual coherence evaluation [Glosser and Deser, 1991; Blonder et al., 1994]. Due to impairment in the episodic memory, AD patients have word-finding difficulties and exhibit a reduced working vocabulary [Nicholas et al., 1985; Ahmed et al., 2013; Appell et al., 1982; Hier et al., 1985; Croisile et al., 1996], which coincide with a poor performance on word fluency tasks [Miller and Hague, 1975]. Despite heterogeneous disease pattern among the patients, anomia is a prominent symptom in AD patients, present even when overall language skills were still intact [Appell et al., 1982; Barker and Lawson, 1968; Bayles and Boone, 1982; Bayles and Tomoeda, 1983; Goodglass, 1980; **?**; Kirshner et al., 1984]. Anomia is one of the earliest and most obvious speech deficits in AD [Kirshner et al., 1984] causing patients to use more circumlocutions [Appell et al., 1982; Bayles et al., 1989; Obler, 1981] or to substitute terms by more generic, neighboring, or indefinite ones as well as to use more deictics [Appell et al., 1982; Nicholas et al., 1985]. Decreased information content [Ahmed et al., 2013; Croisile et al., 1996; Forbes-McKay and Venneri, 2005; Giles et al., 1996; Appell et al., 1982], fewer content elements, and more semantic jargon [Appell et al., 1982] make their speech seem "empty" [Nicholas et al., 1985].

Language deficits in AD are usually reported to affect vocabulary, semantics, and pragmatics only, while syntax and phonology stay unimpaired until the later stages of the disease [Appell et al., 1982; Whitaker, 1976; Schwartz et al., 1979; Bayles and Boone, 1982; Kempler et al., 1987; Bayles et al., 1987; Hier et al., 1985; Murdoch et al., 1987]. In extreme cases, impaired phonology can result in mutism [Kirshner, 2012].

Syntactic deficits manifest themselves in reduced syntactic complexity [Ehrlich et al., 1997; Croisile et al., 1996]. However, other studies did not find a significant difference in syntactic complexity or correctness between AD and healthy controls (HC) with respect to spontaneous speech [Glosser and Deser, 1991; Kempler et al., 1987].

Ehrlich et al. [1997] found a reduced utterance length on narrative tasks which was also reported by Croisile et al. [1996] on a picture description task. Irigaray [1967] also observed the use of inappropriate verb tenses in AD patients.

On the pragmatic language level, the use and comprehension of metaphors, sarcasm, irony deteriorates relatively early in the disease progression [Critchley, 1984; Rapp and Wild, 2011]. Furthermore, AD patients tend to digress from the topic more easily [Obler, 1981].

Several studies found a higher incidence of phonetic and semantic paraphasias in AD speech [Nicholas et al., 1985; Appell et al., 1982]. Repetitions become more common as the illness progresses [Croisile et al., 1996; Nicholas et al., 1985], and echolalia[2] is also observed [Appell et al., 1982].

Naming tasks, as shown for example in [Martin and Fedio, 1983], are a suitable means to detect AD, as the performance declines already early in the disease progression [Kirshner, 2012], even when language, by other measures, appears to be unimpaired [Kirshner et al., 1984]. AD patients show more deficits in semantic fluency tests[3] than in phonemic fluency tests[4] compared to HC [Salmon et al., 1999; Monsch et al., 1992], which is supported by a meta-analysis of 153 studies by Henry et al. [2004]. Findings that the difficulty depends on the parts of speech might apply to spontaneous or elicited connected speech as well and should be further investigated, as there are disagreements in the literature. Robinson et al. [1996] and Fraser et al. [2016] found that AD patients had more difficulty naming verbs than nouns in a picture-naming, and a picture-description task, respectively. Several other studies confirmed that there are fewer verbs in AD speech than in the speech of HC [Saffran et al., 1989]; whereas, Jarrold et al. [2014] observed more verbs, pronouns, and adjectives and fewer nouns.

[2]Echolalia is the repetition of another person's phrases and noises.

[3]The semantic verbal fluency test entails the generation of words from a given category within a limited time frame of usually 60 seconds.

[4]The phonemic fluency test entails the generation of words with a given initial letter within a limited time frame of usually 60 secconds.

2.2.2 Mild cognitive impairment

Mild cognitive impairment (MCI) is a syndrome in the preclinical phase of dementia [Negash et al., 2007] and is an important indicator of diseases such as AD as its symptoms can be detected years before AD is diagnosed [López-de-Ipiña et al., 2013]. In amnestic MCI, where the memory of the patient is impaired, the risk of developing AD is high [Ritchie and Touchon, 2000; Morris, 1997]. An early diagnosis of MCI and treatment help to slow the progression before irreversible brain damage occurs [König et al., 2015] and to delay the onset of other symptoms [Kálmán et al., 2013]. Peintner et al. [2008] even predict that there will soon be disease-modifying treatments for dementia, which will be most effective at the beginning of the disease. However, MCI often remains undiagnosed [Boise et al., 2004] because clinical tests are expensive and invasive, and therefore, are applied only to patients already in a moderate stage of the disease [López-de-Ipiña et al., 2015a].

MCI has a similar influence on speech as dementia. Patients have word retrieval difficulties [Laske et al., 2015; Dos Santos et al., 2011; Cardoso et al., 2014; Fraser et al., 2014; Garrard et al., 2014], which cause a reduced speech rate with more and longer hesitations and pauses [Satt et al., 2014; Jarrold et al., 2014; Horley et al., 2010; Martínez-Sánchez et al., 2012].

Anomia can also lead to a significant difference in the frequency and proportion of the parts of speech [Garrard et al., 2014; Fraser et al., 2014; Baldas et al., 2010]. Furthermore, MCI patients have verbal fluency difficulties [Burhan et al., 2016; Jarrold et al., 2014; Tóth et al., 2018; Manouilidou et al., 2016; Dos Santos et al., 2011].

Finally, more voice breaks [Meilán et al., 2012, 2014] and more phonemic paraphasias [Burhan et al., 2016; Jarrold et al., 2014; Tóth et al., 2018; Manouilidou et al., 2016; Dos Santos et al., 2011] have been reported in the speech of MCI patients.

2.3 Autism spectrum disorder

Autism spectrum disorder (ASD) is a neurodevelopmental disorder characterized by impaired reciprocal social behavior (RSB)[5] and the restricted, ritualistic interest in one specific topic [American Psychiatric Association, 2013].

RSB and the comprised communication impairment in children with ASD are dis-

[5] RSB denotes the ability to process social information, to comprehend the message being conveyed and to respond appropriately in interpersonal interactions.

played by a use of language that differs from neurotypical children. Since the first definition of ASD by Kanner [1943], atypical language has been mentioned as one of the disease's core symptoms and is still used as an important indicator to detect autism [Rutter et al., 2003]. Impairments in language discourse skills, such as having difficulty inititating and maintaining a conversation [Capps et al., 1998; Tager-Flusberg and Anderson, 1991] or having difficulty following discourse conventions such as turn taking or choosing the right register [Malberg and Rosenberg, 2017; Volden et al., 2009] have been investigated by analyzing spontaneous speech. In other studies, narratives, for instance elicited in a retelling task, are used to discover differences between children with ASD and typically developing (TD) children, such as lack of inclination or ability to convey experiences through narrative [Feldman et al., 1993; Loveland et al., 1990; Loveland and Tunali-Kotoski, 2005]. Tager-Flusberg et al. [2005] found that the communication of children with ASD differs from that of TD children already at only one year old, for example in that they are less responsive to their name or someone speaking [DiLavore et al., 1995; Osterling and Dawson, 1994], even their own mother's voice [Klin, 1991]. Most children with ASD are not diagnosed before the age of three or four [Tager-Flusberg et al., 2005], but the aforementioned anomalies can help to diagnose ASD even earlier.

The range of speech impairment in ASD is very wide and a significant proportion of the patient population remains mute for their whole life [Tager-Flusberg et al., 2005]. However, early intervention increases the likelihood to acquire speech [Goldstein, 2002], which makes an early diagnosis very advantageous.

There is often a link between impairments concerning communication and those concerning social skills. Yang et al. [2020] manually annotated and compared the conversational speech of ASD and TD subjects and found that individuals with ASD used more expressions of politeness but less those of uncertainty. In addition, their statements contained less information, and they requested information from their conversation partner less often.

Besides impairments concerning communication, language impairment in ASD affects especially semantics and pragmatics [Kjelgaard and Tager-Flusberg, 2001; Volden and Lord, 1991], while syntax, morphology, and phonology are often reported as relatively unimpaired [Eales, 1993; Landa, 2000; Simmons et al., 2014; Diehl et al., 2006; Colle et al., 2008]. However, [Losh and Capps, 2003] and [Prud'hommeaux et al., 2011] suggest that deficits in narrative and conversational quality are partly due to a limited syntactic complexity. Volden and Lord [1991] investigated that the number of developmental syntax errors (errors commonly observed in children acquiring speech) in ASD children did not significantly differ from TD children, but that there was an increase in non-developmental syntax errors (errors not usually observed in language acquisition) and semantic errors (syntactically correct but involving unexpected words). Furthermore, on a phonological level, ASD children exhibit an overall slower speaking rate [Parish-Morris et al., 2016] and a latency to respond [Heeman et al., 2010].

Disfluencies such as pauses or filler words reflect the planning and delivering of speech [Clark, 1994; Levelt, 1989], which make them a possible indicator of ASD, potentially even to distinguish between ASD and DLD [Gorman et al., 2016]. There have been different results concerning the use of filler words in ASD speech: Lake et al. [2011] reported fewer filler words, but Suh et al. [2014] found no difference, and others found differences only in specific types of disfluency, suggesting that those that serve a communicative purpose pose difficulty for people with pragmatic impairment [Lake et al., 2011; Heeman et al., 2010; Fox Tree, 2001]. Because of the supposition that the fillers *uh* and *um* serve different conversational purposes [Clark and Fox Tree, 2002; Fox Tree, 2001], [Prud'hommeaux et al., 2014], [Heeman et al., 2010], and [Parish-Morris et al., 2016] investigated those words' usage in particular and found that ASD children used fewer *um* than TD children. Lake et al. [2011]; Suh et al. [2014] have shown that repetitions are more common in ASD children, whereas revisions are more common in TD children. Disfluencies should be studied further to provide more agreement with the results in English as well as to confirm whether this feature of ASD speech can be transferred to other languages.

Lord et al. [2004] found that some children exhibit a "language regression" where they lose vocabulary they have already known, which appears to be unique to ASD. A more general feature of ASD is a delayed and slower development of speech [Short and Schopler, 1988; Le Couteur et al., 1989], while other skills are only mildly or not at all impaired [Lord et al., 1996], which also distinguishes ASD from other neurodevelopmental disorders.

The presence of restricted repetitive patterns of behavior, interests, or activities is required for a diagnosis of ASD according to American Psychiatric Association [2013]. This preoccupation with specific restricted interests may be reflected in the focus on a particular topic that differs from the conversation's actual topic [Rouhizadeh et al., 2015; Nazeer and Ghaziuddin, 2012]. Despite having the necessary vocabulary and an intact syntax, the speech of ASD children is often described as "nonsensical", "irrelevant", "bizarre", "inappropriate," or "peculiar and out of place" [Kanner, 1946; Bartak et al., 1975; Loveland et al., 1990; Losh and Capps, 2003] due to the idiosyncratic way of using standard words [Volden and Lord, 1991].

The literature mentions a deficit of theory of mind in ASD children [Baron-Cohen et al., 1985, 2000; Frith and Happé, 1994; Klin et al., 1992; Mottron et al., 2006]. Tager-Flusberg [1992] hypothesized that this might be reflected in a reduced use of cognition terms (such as *think*) and found evidence comparing children with ASD and with Down syndrome. A positive relationship between the occurrence of cognition terms and the performance of theory of mind has also been reported by Capps et al. [2000]; Tager-Flusberg and Sullivan [1995]; Ziatas et al. [1998] and might be an interesting factor in the (automatic) diagnosis of ASD.

3 Previous work on computer-assisted diagnosis of medical conditions affecting language

This chapter provides an overview of common computational linguistic methods used to identify medical conditions that have an impact on language.

3.1 Standardized tests

The traditional method to detect speech impairments is to use standardized tests. Semantic fluency tests, for example, are commonly used to detect impairment in executive function, which can be an indicator of multiple different diseases such as AD, ASD, or schizophrenia [Prud'hommeaux et al., 2017]. For a diagnosis of DLD, measured values of mean length of utterance, the number of different words used and so forth, with a certain standard deviation below the mean values are decisive [Hassanali et al., 2012]. Since the mean values depend on the population chosen as the norm, the score's validity is diminished for children with demographic or socioeconomic backgrounds that deviate from the norm [Gabani et al., 2009; Campbell et al., 1997; Dollaghan and Campbell, 1998]. In addition, Plante and Vance [1994] criticized that norm-referenced approaches may result in both over- and underidentification.

Standardized tests are usually not appropriate to investigate language development over a longer period of time as familiarity with the test influences the performance of the subjects [Fraser et al., 2014].

Furthermore, changes might not be reflected in standardized tests but can be quantified by analyzing natural speech [Fraser et al., 2014]. Another general issue with such traditional methods is that the evaluation of such tests can be very time-consuming and expensive. However, an early diagnosis is crucial for the best treatment of any kind of speech or language impairment. Especially in the case of dementia, screening large parts of the elderly population might be very beneficial to detect and treat potential patients as soon as possible. Therefore automating these tests is highly desirable.

3.2 Computational linguistic methods

There have been several different approaches using computational linguistic methods to explore the potential of computer-assisted ASD diagnosis. Prud'hommeaux et al. [2017] automated the evaluation of semantic fluency scores by combining ontological resources and distributional semantic methods to replace manual annotation. In ASD language, meaningful, yet unexpected words appear significantly more often compared to neurotypical language [Rutter et al., 2003; Rouhizadeh et al., 2013], and diagnostic instruments such as the Autism Diagnostic Observation Schedule [Lord et al., 2000] apply unusual word use as a diagnostic criterion [Prud'hommeaux et al., 2011]. How surprising a word is can be measured using word association measures such as the tf-idf or log odds ratio. The higher the score for a word, the more unrelated it is to its context [Prud'hommeaux et al., 2011]. Losh and Gordon [2014] applied latent semantic analysis to observe semantic differences between children with and without ASD and found significant differences only in a more demanding narrative recall task, but not when narrating from a picture book. On the other hand, Goodkind et al. [2018] used vector semantics to compare narratives of ASD and TD children on a semantic level and found that those of ASD children differ more from the mean of TD children, even with subsampling to eliminate a bias from different transcript lengths. Mirheidari et al. [2018] used word vector representations as well but to detect signs of dementia in spoken language. Prud'hommeaux and Rouhizadeh [2012] used word alignment, a method typically used in machine translation, to automatically measure how far a child wanders from the topic of a story retelling task in order to identify potential ASD. To that end, they measured the percentage of content words in the child's narrative that did not appear at all in the full source narrative. In the same study, the authors calculated the log odds ratio for each word in the retelling. A high mean of that score indicates an abundance of unexpected words, which suggests either a digression from the original narrative's topic or difficulty finding appropriate words. Language models, also typically used in machine translation algorithms to estimate the probability of a given word sequence, have been shown to be effective in identifying norm-deviant language in DLD [Gabani et al., 2009; Solorio and Liu, 2008] and MCI [Roark et al., 2007].

3.3 Machine learning and neural networks

Diagnosis can be considered a classification task that can be solved using machine learning (ML). Common approaches use either automatic speech recognition (ASR) to automatically transcribe speech from interviews or narrative tasks [Fraser et al., 2014; Garrard et al., 2014; Mirheidari et al., 2018] or acoustic features from audio recordings directly. Acoustic features are used where phonological anomalies such as slower speech tempo and hesitations in MCI are relevant for a diagnosis [Tóth et al., 2018]. Rouhizadeh et al. [2015] used a set of existing semantic similarity measures in the context of automatic ASD diagnosis, such as the cosine similarity score, Jaccard similarity coefficent, BLEU score, and WordNet-based vector similarity to show the idiosyncratic way in which the retellings of children with ASD differ from those of neurotypical children. Chojnicka and Wawer [2020] used the linguistic category model[1] to quantitatively analyze the usage of words with emotional polarity in children with and without ASD. A popular tool is the Weka toolkit [Holmes et al., 1994], which is an open-source collection of different ML algorithms used for example by Tóth et al. [2018], Hassanali et al. [2012], Jarrold et al. [2014], and Gabani et al. [2009]. Evaluation is often based on the comparison to benchmark random guessing and naive learner guessing[2] [Jarrold et al., 2014]. There are ML models that use surface-level features, such as measures of language productivity and vocabulary knowledge, to make a diagnosis or, in ML terms, to classify a text. Gabani et al. [2011] proved this approach to be a successful baseline for the identification of DLD, and Lehr et al. [2012] achieved results comparable to the manual evaluation of the Wechsler Memory Scale[3] to identify MCI. Hassanali et al. [2012] extended the set of features proposed by Gabani et al. [2011] with deeper NLP features that further improved the model's performance.

The latest methods have used the concept of a neural network (NN) for diagnosis tasks based on speech data [Beltrami et al., 2016; Ammar and Ayed, 2018; López-de-Ipiña et al., 2017; Mirheidari et al., 2017]. Depending on the task and the training data, different ML methods were found to perform the best.

[1] This model classifies predicates on a scale from abstract to concrete and is a tool for systematic analysis of language.

[2] Naive learner guessing always chooses the most common category.

[3] The Wechsler Memory Scale consists of seven tests that test a person's memory functions.

Generally, simpler ML and NN architectures are suitable for automatic diagnosis because such speech data is sparse. De la Fuente Garcia et al. [2020] reported that support vector machines are used most often because they do not require as much annotated data as others, while still performing well. To make the most efficient use of the available data, it is advisable to apply leave-one-out cross-validation in order to train the model on all of the available data as undertaken by Hassanali et al. [2012]. Besides the distinction between subjects with and without a clinical condition, ML has been applied to differential diagnosis, for example, to distinguish different dementia subtypes or stages [Jarrold et al., 2014; König et al., 2015; López-de-Ipiña et al., 2015a] and also to investigate the development of a clinical condition's impact on language by comparing different age groups as shown by Prud'hommeaux et al. [2014] for ASD.

ML methods have been widely shown to be able to predict a condition with high accuracy even on rather small datasets and, therefore, are promising as diagnostic tools in the future [Solorio, 2013]. However, it is still a long way to incorporate such techniques into clinical applications [Solorio, 2013]. Finally, medical data is highly sensitive and needs to be handled with care.

4 Annotation pipeline for speech therapists

This chapter describes the functionality of the annotation pipeline developed as part of this thesis from an audio recording to data ready to be used in ML algorithms. It is the backend part of an annotation platform that is still under development. The goal is to provide such a platform on one hand for speech therapists to profit from automatic transcription in order to perform manual analyses and, on the other hand, to collect transcribed and annotated speech data to train ML models. The primary but not necessarily exclusive use of the platform will be to annotate the speech of children with DLD. However, it is flexible enough to be used to annotate the speech of individuals with other speech impairments as well.

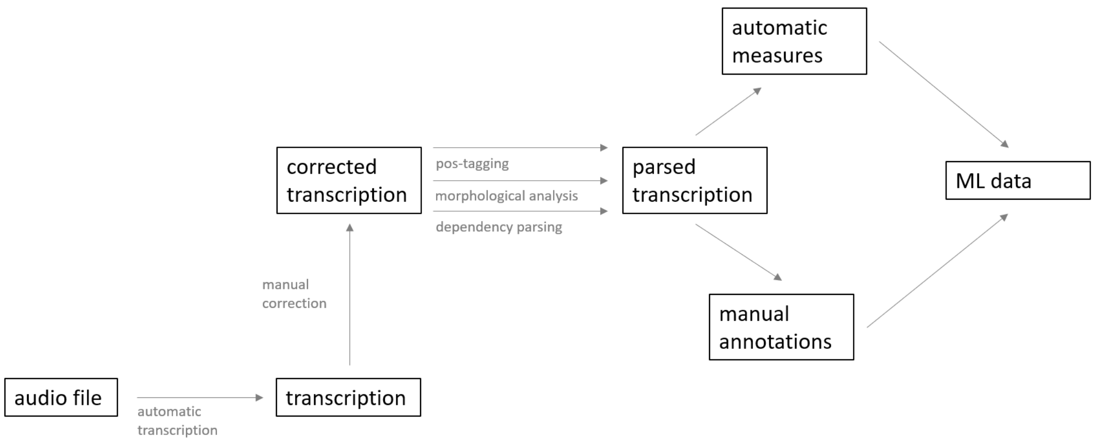

Figure 1: Overview of the pipeline.

The code can be found on GitLab[1].

[1] https://gitlab.uzh.ch/sophia.conrad/ba

4.1 Automatic transcription of an audio file

The first processing step is the automatic transcription of an audio file. The Web-based tool used in the pipeline is IMS-Speech from the University of Stuttgart[2]. The system has a comparable performance in terms of the word error rate (WER) to the state-of-the-art ASR system on the same dataset. For example it has a WER of 3.8% on the WSJ eval'92 English dataset where the state-of-the-art system attains 3.5%. On the Verbmobil 1 test dataset in German, IMS-Speech outperforms the state-of-the-art system (12.7%) with a WER of 7.3%.

The German speech recognition model is generic in order to cover a wide range of transcription tasks, but the developers plan to allow user customization, thereby allowing training on specific data to improve its performance Denisov and Thang Vu [2019].

4.2 Manual correction of the transcription

The manual correction of the transcription is critical at this time, because of the lack of punctuation in the automatic transcription by IMS-Speech, which complicates the sentence segmentation and deteriorates the automatic parsing (part-of-speech tagging, morphological analysis, and dependency parsing) that follows. The pipeline calls Prodigy[3], an annotation tool written and customizable in Python, which supports the annotation of audio files. The annotator can listen to the audio file and correct the transcription proposed by IMS-Speech.

[2] https://75474978-c3fa-43a5-aa6c-ee36f2513064.ma.bw-cloud-instance.org/ims-speech/

[3] https://prodi.gy/

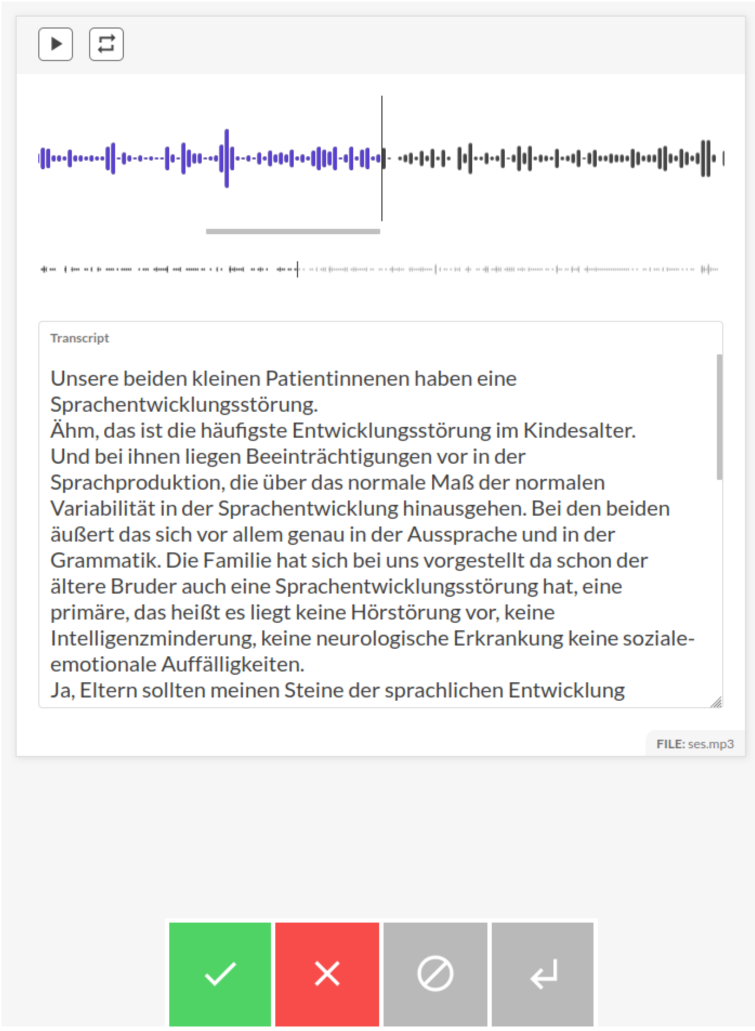

Figure 2: The audio file is loaded in the Prodigy environment and the transcription proposed by IMS-Speech can be modified in the text field.

4.3 Manual annotation

After saving the corrected transcription, Prodigy is called again, loading in one sentence at a time to annotate along with a dependency-parsed representation of that sentence and the morphological analysis of each token, both generated using spaCy[4]. The user is prompted to input the labels to be used before the annotation starts.

[4] https://github.com/explosion/spaCy

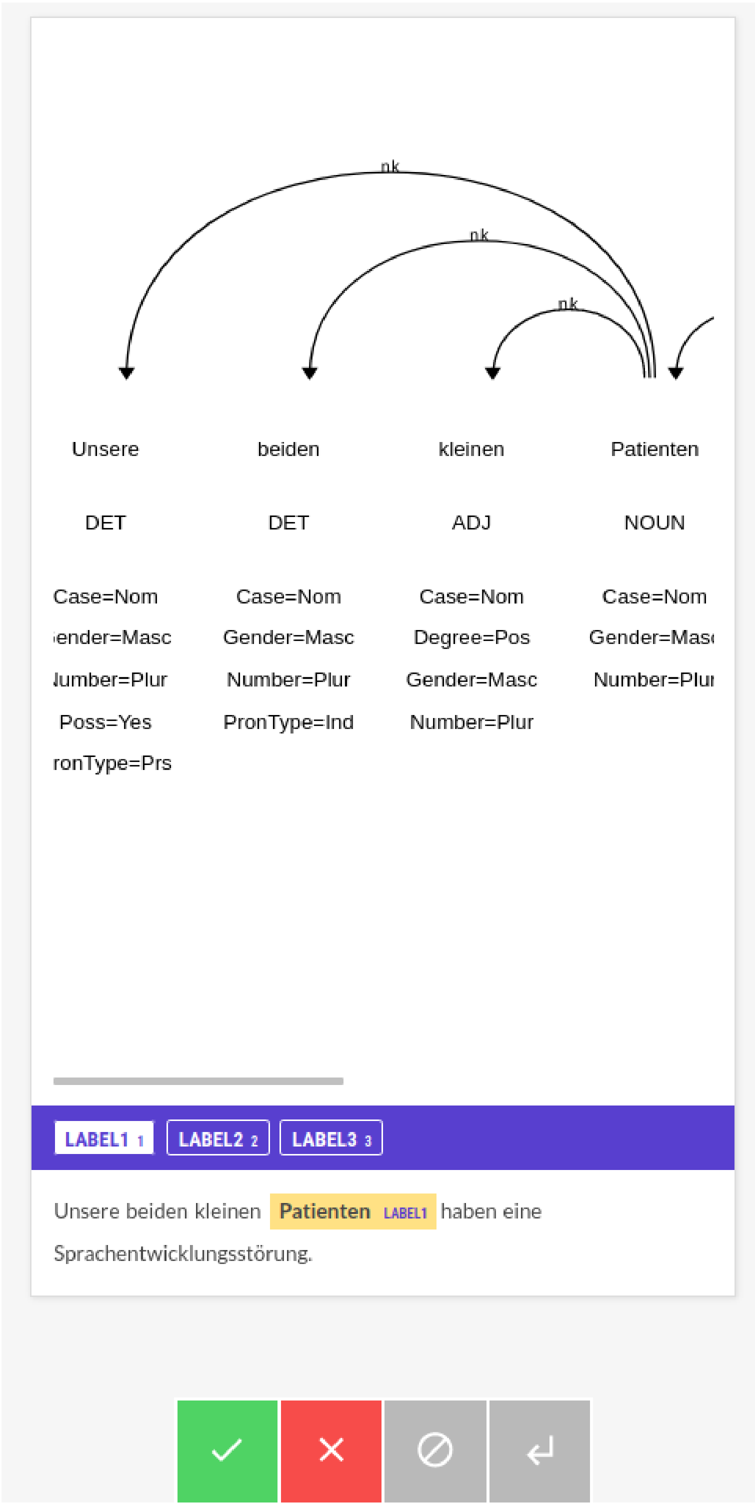

Figure 3: The corrected transcription can be annotated sentence-wise, taking the information from part-of-speech tagging, morphologic analysis, and dependency parsing into account.

The code consists of three separate scripts. To conduct the morphological analysis, the package spaCy 3 is required, which Prodigy does not yet support. Therefore, this part has to be executed separately in another virtual environment where spaCy

3 is installed. After the morphological analysis of the transcription is completed, the user has to switch back to the virtual environment where Prodigy (and spaCy 2) is installed to invoke the third script which opens the annotation interface.

The advantage of using Prodigy as an annotation tool is that it is made to use data for ML. In this case, it can be used to train a classifier that makes a diagnosis based on linguistic features in the future.

4.4 Automatic analysis

Certain linguistic features that can be computed automatically from the corrected audio transcription to use along with the manual annotations for ML. Presently, the mean length of sentences in tokens, different measurements of lexical diversity, and a measure of lexical density are implemented. As mentioned in Chapter 2, the distribution of the parts of speech might differ in certain diseases from HC. The number of each part-of-speech tag is computed for further investigation.

4.4.1 Lexical diversity

A lower lexical diversity can be a useful biomarker for the detection of multiple diseases, such as MCI and AD. There are different ways to measure lexical diversity. All of the possibilities described here along with their advantages and disadvantages are implemented in the pipeline, so users can choose the most appropriate measure for their specific task.

- **Type-token ratio**

The type-token ratio (TTR) is a measure to determine the lexical diversity of a text. The number of unique words (types) is compared to the total number of words (tokens).

$$\frac{number\ of\ types}{number\ of\ tokens} \tag{4.1}$$

The drawback of using the TTR is that it is negatively impacted for long utterances because the longer a text, the greater the likelihood of a word having already occurred Voleti et al. [2019].

- **Moving-average type-token ratio**

To avoid the negative impact for longer utterances, Covington and McFall [2010] introduced the moving-average type-token ratio (MATTR) that calculates the average of TTR scores, which are calculated for a sliding window over a defined number of tokens. The MATTR is length independent, but it is less accurate as it evaluates TTR only locally on sections instead of globally on the whole text.

- **Brunét's index**

Brunét's Index and Honoré's statistic both use all the samples in contrast to MATTR. Brunét's Index solves the length-dependence issue of TTR by using an exponential function.

$$BI = number\ of\ types^{number\ of\ tokens^{-0.165}} \tag{4.2}$$

A smaller Brunét's Index value corresponds to a higher lexical diversity.

- **Honoré's statistic**

Honoré's statistic uses a logarithmic function. Moreover, it rewards texts with more unique words (denoted by V1) with higher scores.

$$HS = \frac{100 * log(number\ of\ tokens)}{\frac{1-V1}{number\ of\ types}} \tag{4.3}$$

4.4.2 Lexical density

The lexical density of an utterance is an important factor in cognitive assessment and is relevant in the automatic detection of different diseases. A common way to calculate the lexical density is the proportion of content words[5] that carry more information than function words[6] with respect to all words Voleti et al. [2019].

$$cd = \frac{number\ of\ nouns + verbs + adjectives + adverbs}{total\ number\ of\ words} \tag{4.4}$$

In the implementation with spaCy, nouns are counted including proper nouns.

[5] nouns, verbs, adjectives, and adverbs

[6] for example prepositions, conjuctions, and interjections

5 Conclusion and outlook

The linguistic indicators of medical conditions involving language impairment have been studied extensively for English. All levels of linguistic structure, that is, phonology, lexicography, syntax, pragmatics, and semantics can be affected. Except for the investigation of phonological anomalies, irregular speech patterns are quantified based on a transcription.

Many different approaches were found to be useful for the automatic analysis of speech data in other languages summarized in Chapter 3. Considering their rapid progress, ML and artificial intelligence are very promising approaches to further automatic diagnosis. Due to the current scarceness of data from speech-impaired individuals, it is advisable to train simpler ML models such as support vector machines or naive Bayes classifiers that perform relatively well on small datasets.

The pipeline developed and presented in Chapter 4 is a prototype for an annotation platform intended for speech therapists. Several aspects should be further developed in order to achieve the two main goals of collecting German data from impaired speakers and training a ML model with the data.

To date, the morphological analysis has to be executed separately from the rest of the process, because it requires spaCy 3, which Prodigy does not yet support. With the next Prodigy release, spaCy 3 will be supported and can be incorporated in the pipeline[1].

Coreference analysis as an additional parsing step might be useful for automatic measures of cohesion and might be implemented using the coreference resolver for German from Zurich (CorZu)[2].

To detect impaired speech, it might be useful to measure the length of utterances in morphemes. This requires compound splitting and morpheme extraction, which are not supported in the analyzer implemented currently, but will be considered for

[1] Features of the upcoming Prodigy release have been announced: `https://support.prodi.gy/t/prodigy-nightly-spacy-v3-support-ui-for-overlapping-spans-improved-feeds-more/3861`.

[2] `https://github.com/dtuggener/CorZu`

implementation in the future.

The correct use of verb-second (V2) word order in main clauses and verb-first (V1) word order in subordinate clauses is an important indicator of the language acquistition stage in German [Schöler and Welling, 2007], and its quantitative measure is planned to be implemented in the next version of the pipeline.

Another addition to the pipeline might be audio segmentation to learn directly from audio files without transcription and to evaluate acoustic and phonological features such as pause rate and speech tempo.

Other possible improvements to be considered are adding a manual correction of the automatic parsing to obtain more accurate data that will be used for ML eventually.

Adapting of the pipeline for the annotation and analysis of Swiss German speech samples is very important, because speech therapy for younger children whose mother tongue is Swiss German and who might not have learnt High German yet is conducted in Swiss German. To that end, all language-dependent components of the existing pipeline have to be replaced. For the automatic transcription, the ASR system by Nigmatulina and Kew[3] is state-of-the-art for Swiss German dialects. There is a Swiss German dependency parser[4] that uses a parts-of-speech tagger[5] trained on NOAH's Corpus[6] [Hollenstein and Aepli]. Baumgartner presents a morphological analysis system for Swiss German intended to be run with the Helsinki Finite-State Transducer Technology [Lindén et al., 2009].

Finally, it is planned to embed the pipeline in a graphical user interface to create a platform that encourages speech therapists to use it. This will confidently lead to enough parsed, annotated, and automatically analyzed data to finally train a classifier for diagnosis – the ultimate goal of this project.

[3] `https://github.com/yunigma/Kaldi-for-ASR-of-Swiss-German`

[4] `https://github.com/DKlaper/gsw-DepParser`

[5] `https://code.google.com/archive/p/hunpos/`

[6] Demo: `https://noe-eva.github.io/NOAH-Corpus/demo.html`

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