Effective weakly supervised semantic frame induction using expression sharing in hierarchical hidden Markov models

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Abstract

We present a framework for the induction of semantic frames from utterances in the context of an adaptive command-and-control interface. The system is trained on an individual user's utterances and the corresponding semantic frames representing controls. During training, no prior information on the alignment between utterance segments and frame slots and values is available. In addition, semantic frames in the training data can contain information that is not expressed in the utterances. To tackle this weakly supervised classification task, we propose a framework based on Hidden Markov Models (HMMs). Structural modifications, resulting in a hierarchical HMM, and an extension called *expression sharing* are introduced to minimize the amount of training time and effort required for the user.

The dataset used for the present study is PATCOR, which contains commands uttered in the context of a vocally guided card game, *Patience*. Experiments were carried out on orthographic and phonetic transcriptions of commands, segmented on different levels of n-gram granularity. The experimental results show positive effects of all the studied system extensions, with some effect differences between the different input representations. Moreover, evaluation experiments on held-out data with the optimal system configuration show that the extended system is able to achieve high accuracies with relatively small amounts of training data.

1 Introduction

The use of vocal interfaces in our daily lives is becoming more common: we can talk to our smartphones through Siri, computers, smart-TV and other specialized domestic devices, such as Alexa and Echo. People with physical disabilities, for whom manual operation of such devices requires exhausting effort, could greatly benefit from such a hands-free control interface. However, many people with physical disabilities additionally have speech disorders, since motor impairments can also affect the control of the speech articulators. This makes accurate speech recognition very difficult. Still, case studies have also shown that, despite a speech disorder, some users find it easier to use a speech recognizer than a keyboard or a switch-scanning system (Chang, 1993; Hawley et al., 2007).

In the ALADIN project[1], we aim to develop a speaker-dependent, adaptive vocal interface for home automation, in which the vocabulary and command structures are not predefined, but rather automatically induced by the system. This allows users to address the system in an intuitive way, choosing their own commands. The system is language independent and can adapt to regional or pathological features of the user's speech. The vocal interface is trained in an initial training phase in interaction with the user, and keeps adapting to new data that are automatically collected during the usage phase. This constant adaptation makes the system very appropriate for people with progressive diseases.

During the training phase, spoken commands are associated with executed controls, which are represented as semantic frames that encode the relevant properties of the actions. An action such as pressing the button "4" on the TV remote control, associated with the spoken command "switch the TV to channel four", is represented by a frame of the type `change_channel`, containing the slots <`device`> and <`channel`> and their respective values `TV` and `4`.

A semantic frame induction engine (*FramEngine*) then looks for recurring patterns in the commands – which may be words, morphemes and/or other units – and relates them to slots and their values in the associated semantic frames. This induction task is weakly supervised, as there is only supervision at the utterance level: no relations between parts of the utterances and parts of the semantic frames are specified in advance. An important requirement for the ALADIN system is that it needs to be able to learn these relations on the basis of a small set of training instances, since the amount of effort required from the user to train the system should be kept to a minimum.

In previous work (Ons et al., 2013), we presented the standard semantic frame induction system (*FramEngine*) that has been developed in the ALADIN project, and demonstrated the performance of an early implementation of this system with non-pathological and pathological speech input. The results show that the system has a promising learning potential with small amounts of training data, but that enhancements are needed in order to produce practically usable accuracies for more complex utterances. Improvements can be made both in the acoustic processing and in the way semantic frames are induced from the utterance. This paper focuses on the latter problem and studies the effect of extensions to the original Hidden Markov Model approach when trained and evaluated on the basis of **transcribed** command utterances.

Factoring out the acoustic complexities of the task allows us to evaluate the semantic frame induction framework in optimal conditions and observe what is minimally needed to reliably bootstrap semantics from a signal. In this chapter, we consider different degrees of complexity and vary the granularity of the transcription (lexical vs. sub-lexical vs supra-lexical). Experiments with transcribed data thus

[1] http://www.aladinspeech.be

allow us to set an upper bound to what can be expected of semantic frame induction when it is applied to acoustic signals. In addition, using textual rather than acoustic input enables a more thorough qualitative analysis of the system's performance, since the identities of the command segments – text segments rather than acoustic patterns – are readily observable. In particular, the produced mappings between the command segments and the slots and values in the semantic frames can be inspected in detail.

Our aim is to find an appropriate level of generalization: the system should not merely learn to map full utterances to full semantic frames, but rather learn associations between parts of the utterances and parts of the semantic frames and be able to make inferences about new combinations of such parts, which have not been encountered in the training data. Furthermore, we will not only focus on achieving the highest possible classification accuracy, but also on finding out which experimental conditions minimize the amount of training time needed to achieve workable results for the user. We will therefore rely extensively on learning curve experiments to evaluate the proposed techniques against the backdrop of the self-learning, adaptive command-and-control interface envisioned by the ALADIN project.

In this case study, we use a dataset of commands and semantic frames for a voice-controlled version of the card game *Patience*. This is an appropriate application in a domestic context with an interesting level of complexity, as the vocabulary needed to play Patience is fairly limited, but being able to model more complex aspects such as word order, is crucial in determining the nature of the card moves, i.e. the meaning of the commands. This makes the Patience task more complex than typical home automation tasks, such as the control of lights, heating or the television, which only require keyword spotting for successful semantic frame induction.

We will start this paper with a description of the task of semantic frame induction in general and the standard ALADIN approach in particular in Section 2. We will describe the data for our case study in Section 3. The extensions to the architecture are presented in Section 4, while Section 5 outlines the research questions that are addressed in this paper and present the experimental setup to answer them. This is followed by a discussion of the experimental results in Sections 6 and 7, after which we present our conclusions and plans for future research in section 8.

2 Semantic Frame Induction

The task of inducing semantic representations from utterances is well studied in the context of natural language database querying. (Zettlemoyer and Collins, 2005) describe an approach based on Probabilistic Combinatory Categorial Grammars to tackle the problem. Their research highlights the need to move beyond what a traditional HMM-approach is capable of. This point is also made by (Chen and Mooney, 2011), who describe how a semantic parser can be automatically built by observing human actions.

The work presented in this paper differs from these research efforts in that the ALADIN approach is designed to be applicable to acoustic, as well as textual units. As such, it is more akin to research efforts in the context of spoken language understanding (SLU), many of which use semantic frames (Wang et al., 2011), or at least a representation that can be easily converted into such a frame-based representation.

Various semantic frame induction approaches have been investigated, based on *fully aligned* training data in which all the slots in the semantic frames have been aligned with their corresponding word(s) in the utterances. When non-hierarchical semantic representations are used in such a *supervised* context, the semantic frame induction task is essentially a supervised sequence labeling task, akin to "concept tagging", in which the words of an utterance are tagged with concepts (slots) from the semantic representation. (Hahn et al., 2011) apply a variety of discriminative and generative techniques to perform concept tagging of transcribed speech corpora (Bonneau-Maynard et al., 2009; Mykowiecka et al., 2009; Dinarelli et al., 2009). Previous work in the ALADIN project similarly applied an exemplar-based supervised concept tagging method, using manually tagged PATCOR (cf. Section 3) utterances as training data (van de Loo et al., 2012).

In the work presented here, we use a generative concept tagging approach, with a lower level of supervision. In most generative concept tagging models, hidden concept sequences are modeled with a concept n-gram model and each concept state in the sequence generates a word sequence according to another model, which (Wang et al., 2011) call the lexicalization model. An early generative model used for concept tagging was the hidden semi-Markov model by (Pieraccini et al., 1991). This model was applied to the Air Travel Information System (ATIS) dataset (Hemphill et al., 1990; Dahl et al., 1994). In (Pieraccini et al., 1991), the lexicalization model was a word n-gram model, conditioned on the concept state. With n=1, this results in a classical hidden Markov model (HMM); with n>1, this is a hidden semi-Markov model (HSMM). The HMM model in the default configuration of ALADIN (Section 2.1.2) corresponds to the n=1 version of their model. However, in our model, we use slot values as concept states, while in (Pieraccini et al., 1991), the concept states correspond to slots, as in most concept tagging systems. In most systems, the slots are first induced through a concept (=slot) tagging process, and the slot values are added in a separate post-processing step. In ALADIN's decoding process, on the contrary, the command units are directly tagged with slot values, which eliminates the need for additional post-processing.

The models discussed above were all applied to *supervised* concept tagging tasks. In the experiments described in this paper, such alignments will not be available. For concept tagging based on *unaligned* data, some generative methods based on statistical machine translation (SMT) techniques have been used, in which the alignment between words and concepts is explicitly modeled, using expectation maximization for parameter optimization (Epstein et al., 1996; Della Pietra et al., 1997; Macherey et al., 2001).

It is important to note, however, that in the experiments described in (Epstein et al., 1996) and (Macherey et al., 2001), most words expressing concepts were replaced with class names (such as CITY), thereby constraining their possible alignments to concepts. Such prior class member information is also not available in the ALADIN training situation. Since the command input in the final ALADIN system

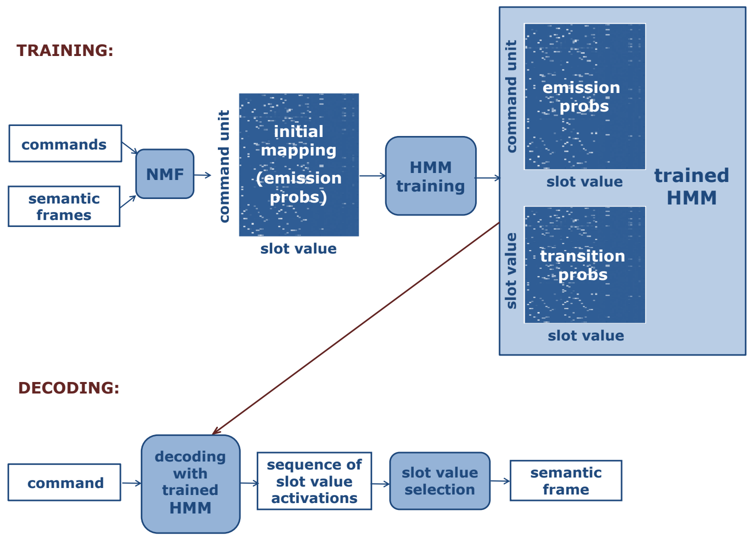


Fig. 1. The ALADIN framework.

will consist of anonymous categorical 'word' units, rather than known lexical items, no prior lexical information can be used to constrain the alignments.

In all of the aforementioned approaches, all concepts in the annotations were assumed to be expressed in the utterances. In the ALADIN training situation, however, this assumption does not hold: the semantic frames used for training are generated automatically from actions (e.g. button presses or mouse operations), and most of the time contain slot values that are not actually expressed in the associated utterances. In the following subsection, we will describe the basic ALADIN approach to perform frame decoding with a system trained on utterances and their associated semantic frames, very likely to contain redundant information.

Finally, (Goldwasser and Roth, 2014) describe work on learning natural language interpretations without direct supervision. While they also apply their technique to the case study of *solitaire*. The approach is however completely different from ours, as their goal (and the learning mechanisms to reach it) is framed in the context of learning to play the game legally, rather than to model a user's vocabulary and grammar.

2.1 The ALADIN approach

An overview of the ALADIN semantic frame induction framework is shown in Fig. 1. In the **training phase**, the user speaks a set of commands, and for each command simultaneously executes the associated action on the device or application. The actions are automatically converted into action frames: semantic frames in which all the relevant properties of the action are represented in the form of slots filled with values (see Fig. 4(b) for an example). Based on this set of spoken commands and their corresponding action frames, an HMM is trained in which the command structures and their relations with the semantic frame structures are modeled. HMM training is preceded by a non-negative matrix factorization (NMF) phase, in which an initial mapping between the slot values in the semantic frames and the observable units in the commands is produced. This initial mapping serves as an initialization of the HMM's state emission probability distribution.

During **decoding**, commands spoken by the user are decoded into sequences of slot value activations, using the trained HMM. Based on these sequences, semantic frames are generated that contain the information on the basis of which the application can execute the corresponding actions. The framework will be described in more detail in the following subsections.

2.1.1 Non-negative matrix factorization (NMF)

The first step in the training process is to produce an initial mapping between units in the commands and slot values in the semantic frames. This is accomplished through NMF, a method that factorizes matrices as the product of two low-rank matrices, using non-negativity constraints (Lee and Seung, 1999). Given a matrix V with dimensions [M x N], NMF approximately decomposes it into a matrix W with dimensions [M x R] and a matrix H with dimensions [R x N].

When spoken commands are used as input, NMF is used to discover recurring acoustic patterns (e.g. word-like units) in the signal, using the semantic frames as grounding information. The process is depicted in Fig. 2(a). The input consists of two matrices: V_{frames} and V_{commands}. V_{frames} contains the frame supervision: each command column consists of a binary vector of slot value activations, which represents the associated semantic frame. V_{commands} contains the activation levels of the acoustic units that are observed in each command: each entry contains the activation level of an acoustic unit in a command.

The two V matrices, V_{frames} and V_{commands}, are vertically concatenated, as shown in Fig. 2(a), and decomposed into two W matrices, W_{frames} and W_{commands}, and one H matrix. The columns in W_{frames} and W_{commands} represent discovered latent acoustic patterns. W_{frames} contains the associations of these patterns with the slot values in the semantic frames, and W_{commands} contains the associations with the acoustic units observed in the commands. The matrix H contains the activation levels of the discovered acoustic patterns in each command. W_{frames} constitutes the initial mapping between the relevant command units – which are now the discovered acoustic patterns rather than the original acoustic units – and the slot values, as shown in Fig. 1. For more details regarding the NMF process for latent acoustic pattern discovery, we refer to (Ons et al., 2014) and (Van hamme, 2008).

In the work presented in this paper, textual input is used instead of audio input, as explained in the introduction. The NMF process is the same as with audio input, as depicted Fig. 2(a), except that the rows in W_{commands} and V_{commands} represent textual units instead of acoustic units, i.e. word or phoneme n-grams. The recurring patterns that are discovered by NMF are not used in our experiments with textual input, because the textual units themselves are the relevant units that should be associated with slot values in the semantic frames. Therefore, we post-multiply

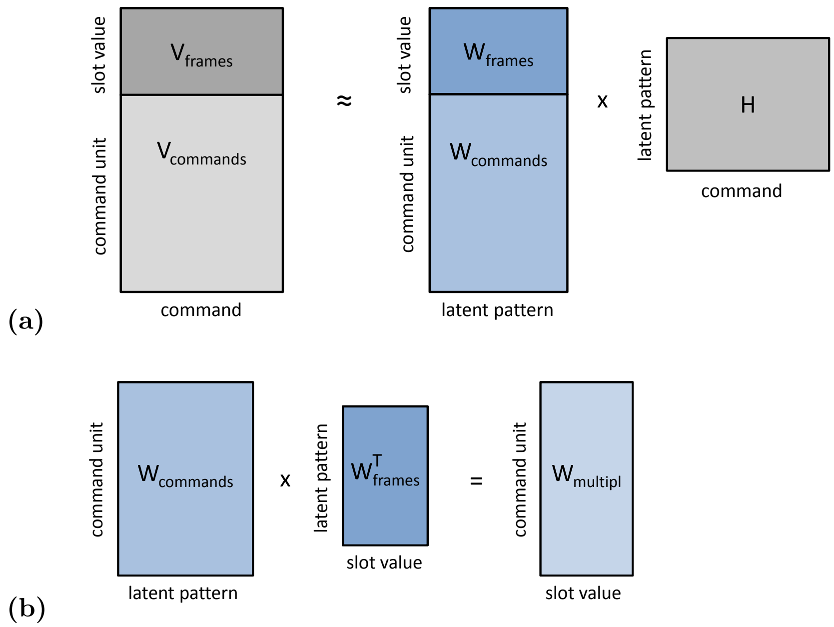


Fig. 2. The NMF process (a) and the post-multiplication of $W_{commands}$ by the transpose of W_{frames} (b). In both (a) and (b), the input is shown on the left-hand side and the output is shown on the right-hand side of the equation.

$W_{commands}$ by the transpose of W_{frames}, as depicted in Fig. 2(b). This results in a matrix $W_{multipl}$, with rows representing textual command units and columns representing slot values in the semantic frames. In our experiments, $W_{multipl}$ is used as the initial mapping between slot values and command units, which is depicted in Fig. 1 as the result of the NMF process.

2.1.2 Baseline HMM

In HMMs, observed sequences are assumed to be generated by an underlying sequence of hidden states. In the HMMs that are used in the ALADIN framework, the commands are the observed sequences (be it acoustic or textual). In the experiments presented in this paper, with textual command input, they are sequences of word n-grams or phoneme n-grams.

The hidden states in the HMM are the slot values in the semantic frames. The basic HMM structure is depicted in Fig. 3. This figure shows the HMM of one semantic frame type. In an application where multiple semantic frame types are used, several of these HMMs are connected in parallel; one for each frame type. The slot value states in the single-frame HMM are almost fully connected. The only transitions that are prohibited, are transitions between slot values that belong to the same slot (apart from self-transitions to the same slot value, which are allowed), and transitions involving slot values that do not occur in the training data. The initial non-zero transition probabilities are uniformly distributed. The

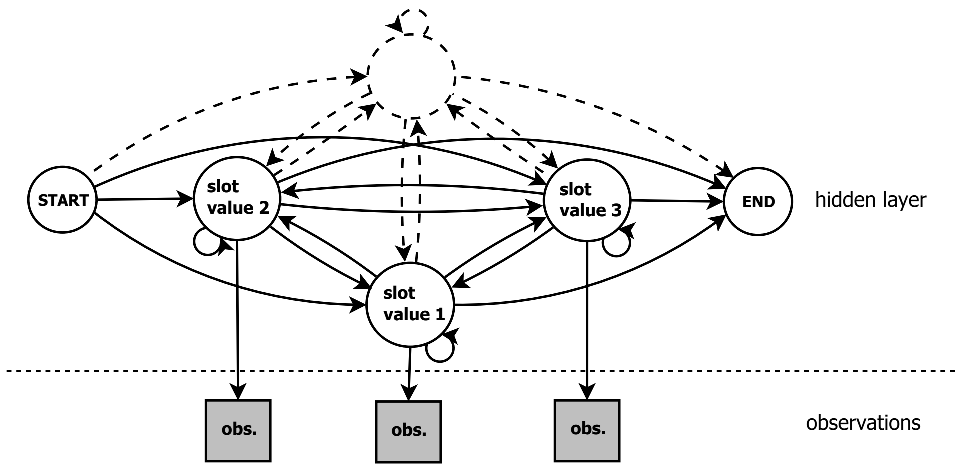


Fig. 3. The basic HMM structure.

transition probability distribution can be represented as a state-by-state matrix of probabilities – in this case, a slot-value-by-slot-value matrix (see Fig. 1).

The transition and emission distributions of the states are the HMM parameters, which are trained in an iterative procedure using the Baum-Welch algorithm (Baum, 1972). This algorithm, which is a specific version of the expectation-maximization (EM) algorithm (Dempster et al., 1977), iteratively alternates between an expectation step (E-step) and a maximization step (M-step). In the E-step, expected state occupancy and transition counts are computed based on the current HMM parameters and the observed sequences; in the M-step, the HMM parameters are updated based on the counts. In ALADIN's HMM training procedure, the semantic frame supervision is used at the end of each E-step: the expected occupancy counts of states (slot values) that do not occur in a given utterance according to the corresponding semantic frame are set to zero, followed by re-normalization.

2.1.3 Decoding

In the decoding phase, the trained HMM is used to decode a command into a sequence of slot values, which is subsequently converted into a semantic frame. First, unknown command units, which have not occurred in the training data, are mapped to the most similar known unit from the training data using ADAPT (Elffers et al., 2005). ADAPT is a dynamic programming algorithm that computes the minimum edit distance between two strings of phonetic symbols, based on articulatory features.

The Viterbi algorithm (Viterbi, 1967) is then used to find the optimal path through the slot value states in the trained HMM, given the command. Since this algorithm produces a single optimal path, which can only include slot values of a single frame type, the frame type is implicitly selected. However, it is possible that multiple slot values for a single slot occur in the resulting slot value sequence

Table 1. PATCOR example transcriptions for "*zwarte drie op rooie vier*" (*black three on red four*). "_" indicates a word boundary.

Orthographic	Phonemic
zwarte drie op rooie vier	zwArt@_dri_Op_roj@_vir

(only *direct* transitions between slot values within the same slot are not allowed in the HMM). In order to select the most probable slot value for each slot, the posterior probabilities of the slot values in the sequence, given the emission probability distribution, are used. These posterior probabilities are accumulated across the sequence, and for each slot, the slot value with the highest total probability is selected. A slot is filled with the selected slot value if its total posterior probability exceeds a certain threshold.

3 Patience dataset PATCOR

The experiments presented in this paper use a vocally guided Patience game as a case study. Patience (also known as Solitaire) is one of the most well-known single-player card games. The playing field (cf. Fig. 4) consists of seven columns, four foundation stacks (top) and the remainder of the deck, called the hand (bottom). The aim of the game is to move all the cards from the hand and the seven columns to the foundation stacks, through a series of manipulations, in which consecutive cards of alternating colors can be stacked on the columns and consecutive cards of the same suit are placed on the foundation stacks.

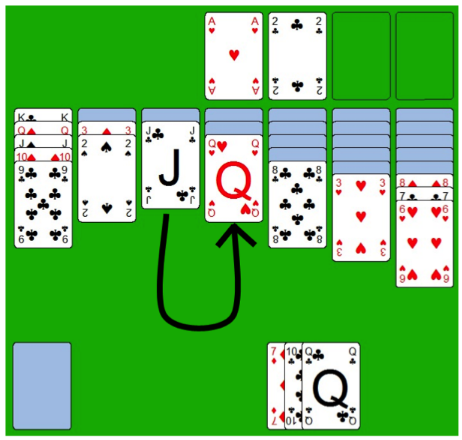
For our experiments, we will make use of PATCOR, a dataset containing recordings of nine speakers playing Patience. In total, PATCOR contains over 3,000 spoken commands, supplemented with command transcriptions, corresponding semantic frames, and representations of game states between the moves. The language of the spoken commands is Belgian Dutch, and the speech is non-pathological.

The speakers' ages range between 22 and 73, and the first eight speakers were balanced for gender and education level. With these eight speakers, around 250 utterances were recorded per speaker. In addition, a larger dataset of over 1,000 utterances was recorded with a ninth speaker, which we will use as our final means of evaluation on held-out data (cf. Section 7). More details about the data set and the command structures that were used by the speakers are described in (van de Loo et al., 2012).

Transcriptions and action frames

The recorded commands were orthographically transcribed by the first author. The orthograpic transcriptions were then converted to phonemic transcriptions, using

Command: *Leg de klaveren boer op de rode koningin*
(English: *Put the jack of clubs on the red queen*)



(a) Command and corresponding action in the playing field

Frame type: `movecard`

Slot	Automatic Slot value	Oracle Slot value
<from_suit>	c	c
<from_value>	11	11
<from_foundation>	-	-
<from_column>	3	-
<from_hand>	-	-
<target_suit>	h	h,d
<target_value>	12	12
<target_foundation>	-	-
<target_column>	4	-

(b) automatic and oracle frames

Fig. 4. Example of a Patience command in PATCOR, the corresponding action on the playing field (a) and the content of of the automatically generated frame and the oracle frame that was added manually (b).

a pronunciation lexicon with only one pronunciation variant per word. The pronunciation lexicon was based on the lexicon of the Spoken Dutch Corpus (CGN, (Oostdijk, 2000)), from which the single pronunciation variants were selected manually. Words not present in the pronunciation lexicon were added manually. The phoneme alphabet used for the transcriptions is YAPA (cf. (Mertens and Vercammen, 1998)), as exemplified in Table 1.

The commands were also annotated with their semantic representations in the form of *action frames*. The action frames in PATCOR are representations of Patience moves, specifying the type of move - the frame type - and a set of attributes in the form of *slots* that can be filled with *values*. The slots and their values specify certain properties of the move, such as the position of the card that is moved and the position that it is moved to.

PATCOR has two frame types: `dealcard` and `movecard`. The two frame types and their associated slots and slot values (if any) are shown in Fig. 5. The `dealcard` frame has no slots; it simply represents the action of dealing a new hand and needs no extra attributes. The `movecard` frame represents a card move from one position to another, and has nine slots. The first five slots pertain to the card that is moved (the `from` slots) and the other four pertain to the card or position that it is moved to (the `target` slots). Cards are specified in terms of suits (`h` for hearts, `s` for spades, `d` for diamonds and `c` for clubs) and values (`1` to `13`, representing ace to king). Card positions are also specified in terms of three areas on the playing field: the columns (`1` to `7`) in the middle, the foundation stacks (`1` to `4`) at the top, and the hand at the bottom (cf. Fig. 4(a)).

Each command in PATCOR has two action frames associated with it: an *automatic frame* and an *oracle frame*. An example of a command, its associated move and its two action frames is shown in Fig. 4. The automatic frame and the oracle frame both have the same frame type and slots, but the slot values that are filled in differ. The automatic frame was generated during the Patience game through the move that was performed by the experimenter. In this frame, all slot values that apply to the performed move, are filled in (see Fig. 4(b)). These are all the relevant properties of the move, which speakers *might* refer to in their commands. The automatic frame is therefore usually overspecified, i.e. containing redundant information not expressed in the command.

The oracle frame, on the other hand, was added manually, and represents the actual content of the command that was spoken (see Fig. 4(c)). This means that only the slots that the command actually refers to, are filled in. In Fig. 4(c), for instance, the card positions are not filled in, because they are not mentioned in the command. In addition, the oracle frame may include multiple slot values for a single slot, in cases where the command is ambiguous. In the example in Fig. 4, the word 'red' is ambiguous as to the value of the slot <`target_suit`>: it can be either hearts (h) or diamonds (d). In such cases, the oracle frame includes all slot values that are possible according to the command; in this case, both `h` and `d` are included in the slot <`target_suit`>.

In the experiments described below the automatic frames will be used to train the systems. The manually created oracle frames will function as gold-standard reference points against which we can evaluate.

4 System extensions

The architecture described in Section 2.1 provides a full semantic frame induction framework, enabling training and decoding with both textual and acoustic com-

Frame type: `movecard`		
Slot		**Slot values**
<from_suit>	(FS)	h,d,s,c
<from_value>	(FV)	1-13
<from_foundation>	(FF)	1-4
<from_column>	(FC)	1-7
<from_hand>	(FH)	1
<target_suit>	(TS)	h,d,s,c
<target_value>	(TV)	1-13
<target_foundation>	(TF)	1-4
<target_column>	(TC)	1-7

Frame type: `dealcard`	
Slot	**Slot values**
-	-

Fig. 5. The two frame types in PATCOR, including their slots and the possible slot values. The full slot names are in angle brackets; the abbreviated slot names are in round brackets. The frame type `dealcard` does not have any slots.

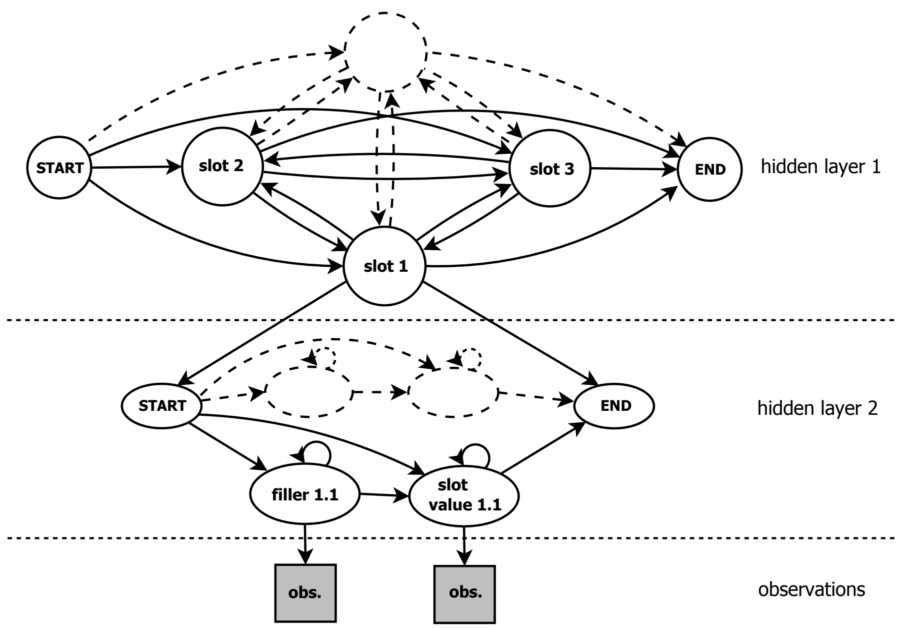


Fig. 6. The modified, hierarchical HMM structure, which includes an extra hidden layer and filler states.

mand input. However, there is much room for improvement of this basic system. In this section, we present some system extensions under consideration in this paper: two enrichments to the HMM structure and a novel technique called *expression sharing*. We will discuss these in the following subsections.

4.1 Slot-based transition probability sharing

In the basic HMM, the hidden layer only represents slot values; these are the values that have to be induced by the system in order to fill in a complete semantic frame. In most commands, however, the underlying command structure is better defined in terms of slot sequences than in terms of sequences of slot values; transition probabilities hold between slots rather than individual slot values. For instance, the transition probability between the slots <`target_suit`> and <`target_value`> should be independent of their specific slot values. This intuition has been implemented in ALADIN's HMM structure by *sharing*, or equalizing, the transition probabilities between all pairs of slot values belonging to a particular pair of slots.

This introduces an extra layer in the HMM, resulting in a *hierarchical* HMM (HHMM), as depicted in Fig. 6: the highest-level hidden layer is now a layer of slot states, where each slot state models a sequence of acoustic events corresponding to at least a word. Each slot state has multiple sub-HMMs that model its different slot values. The states in the slot value sub-HMMs generate observations (command units); slot value states generate command units expressing a specific slot value, and filler states generate so-called *filler units* (cf. Section 4.2).

The gain from this hierarchical architecture is a reduction in the number of transition probabilities to be estimated. Without hierarchy, each slot value can have an arbirary transition probability to the next slot value. In an HHMM, all transitions pass through the non-emitting *START* and *END* states in layer 2 of Fig. 6, hence factorising the full transition matrix into the outer product of two vectors. Sharing HMM parameters in this way reduces the number of parameters to be learned, which should reduce the amount of training data needed. During training, transition probability sharing is carried out after the M-step in each Baum-Welch training iteration, by averaging the re-estimated transition probabilities across shared transitions before normalizing them. Slot values that do not occur in the training set are excluded from sharing.

The HHMM also provides the framework for sharing emission densities, again with the goal of reducung the number of model parameters and hence the training data requirements. Two forms of emission tying are exploited: sharing of *filler states* and *expression sharing.*

4.2 Filler states

These filler states are introduced in order to deal with command units that do not express specific slot values, for instance function words such as determiners or prepositions, and interjections such as 'uh' ('erm') and 'nee' ('o'). Many of these filler units can serve as signal words that indicate certain slot expressions before or after them, for instance in the case of prepositions. In our framework, the filler states are associated with specific slot value states: each slot value state is preceded by a dedicated filler state, which can optionally be skipped.

The filler states have a shared initial emission probability distribution. This initial distribution is produced by adding an extra 'filler unit' column to the matrix

W_{frames} in NMF, which is activated for all commands. In the HMM training phase, the emission probability distributions of the filler states can optionally be shared.

4.3 Expression sharing

In many applications, there are sets of slot values that are very likely to be expressed by the same words. For instance in the Patience application, we can assume that the slot values in the slot <from_suit> are expressed by the same words as the slot values in the slot <target_suit>, e.g. by the words 'hearts', 'spades', 'clubs' and 'diamonds' in English. In traditional approaches, this property is typically not considered during semantic frame slot filling. In this paper, we introduce *expression sharing*, a novel technique to incorporate this knowledge in the system. This is done by *sharing* the associations of these slot values with observed units in the commands. The sets of slots that share their slot value expressions are called *shared expression sets*. Expression sharing can also reduce the amount of training data needed, since it decreases the number of associations between slot values and command units that have to be learned by the system.

In many cases, the shared expression sets that are defined, are sets of slots that are essentially specific instances of a more general slot type. For instance, the slots <from_suit> and <target_suit> can be regarded as instances of a more general slot type <suit>. Expression sharing is therefore akin to the concept of discerning different slot types in the semantic frame definitions, such as the slot types 'City' and 'Date' in the Air Travel Information System (ATIS) domain (Hemphill et al., 1990; Dahl et al., 1994).

In the ALADIN framework, expression sharing can be applied at two different stages in the training process: during the NMF phase and during the HMM training phase. In the NMF phase, expression sharing is applied as follows: when a slot value that is part of a shared expression set is encountered in a training instance, the other corresponding slot values in the shared expression set are activated as well in that training instance. For example, if an instance's semantic frame contains the slot value <from_suit=h>, the slot value <target_suit=h> is also activated in that instance. A complete example is shown in Table 2.

In the HMM training phase, expression sharing is applied by sharing the emission probability distributions of corresponding slot values in a shared expression set. After the M-step in each Baum-Welch pass, the re-estimated emission probability distributions are averaged across the corresponding slot value states (for instance, across the states <from_suit=h> and <target_suit=h>), before they are normalized.

Expression sharing in the HMM training phase is not only applied to sets of corresponding slot value states, but also to sets of filler states. Two options were implemented regarding filler state expression sharing. The first option is to share the emission probabilities across *all* filler states, resulting in one single filler state emission probability distribution. The second option is to share the filler state emission probability distributions slot-wise, which means that the emissions are shared among filler states that belong to the same slot. For instance,

Command: *harten acht op schoppen negen* (**English:** *eight of hearts on nine of spades*)	
Original frame supervision	**Additional frame supervision**
FS=h	TS=h
FV=8	TV=8
FC=2	TC=2
TS=s	FS=s
TV=9	FV=9
TC=4	FC=4

Table 2. Example of expression sharing in the NMF phase: the slot values in the right column are added to the instance's frame supervision.

the emissions of the filler states associated with the slot values <`from_suit=h`>, <`from_suit=s`>, <`from_suit=c`> and <`from_suit=d`> are shared, resulting in one single <`from_suit`> filler state emission probability distribution. The use of slot specific filler state emissions is similar to the use of slot specific preamble and postamble states in (Wang and Acero, 2006); they can serve as contextual clues for identifying the slot.

We can expect expression sharing to be a powerful extension to traditional HMM-driven semantic frame induction. It can typically be applied when concepts that need to be induced, are subtypes of a more general concept (or are used in different contexts). In the context of ATIS (Hemphill et al., 1990), for example, departure city and destination city are both subtypes of a more general concept 'city'. Expression sharing would enable the discovery of this property. While expression sharing is able to solve a number of issues, it does not enable processing quantifiers or the induction of deep hierarchic concept spaces.

5 Experimental Setup

In this paper, we investigate the effect of the system extensions discussed in the previous section on the system's semantic frame induction capabilities. We focus on the following research questions:

1. Do transition probability sharing and expression sharing have the expected positive effect on learning speed, and how large are the effects of the different sharing types?
2. Do these extensions introduce specific decoding errors?
3. How does the introduction of filler states affect the semantic frame induction performance and what effect do the different types of filler state emission probability sharing have?

5.1 System parameters

In order to investigate these effects in controlled conditions, we perform exhaustive experiments with four system variables, based on the extensions discussed in Section 4:

Parameter	Values
Filler states	none, non-shared, all-shared, slot-shared
T (transition) sharing	true, false
E (expression) sharing in NMF	true, false
E (expression) sharing in HMM	true, false

The parameter 'filler states' has four possible values: there can be no fillers ('none'), fillers without emission sharing ('non-shared'), fillers that all share their emission probability distributions ('all-shared'), or fillers that share their emission probability distributions slot-wise ('slot-shared'), which means that the distributions of fillers that belong to the same slot are shared. The other three parameters are booleans. T-sharing (transition-sharing) means that the transition probabilities are shared slot-wise, as discussed in Section 4.1 and depicted in Fig. 6. The two remaining parameters are two different types of expression sharing applied to slot value states in respectively the NMF phase and the HMM phase.

5.2 Decoding methods

Apart from the parameter variation listed in Section 5.1, we also experimented with two decoding methods: NMF decoding and HMM decoding. HMM decoding is the decoding method that was described in Section 2.1.3, using the trained HMM. NMF decoding, on the other hand, is a baseline decoding method in which only NMF is used. This decoding method does not model any information about the temporal ordering of the command units. The matrix with the associations between slot values and command units, which has been produced in the NMF training phase, is used to convert the sequence of command units into a sequence of slot value activations (slot value probability distributions). For each slot value, all activations across the whole sequence are accumulated, and for each slot in each frame, the slot value with the highest accumulated activation is selected, if that activation exceeds a certain threshold. Since this method can result in the selection of slot values from different frames, the frame with the highest accumulated probability mass is selected.

5.3 Command input

We also vary the input type during our experiments, to study the effect of command unit granularity on the performance of the frame induction approach. In the experiments reported here, we only use phonemic gold-standard transcriptions (Table

1 on the right). Different segmentations of the transcriptions are used. The transcriptions were segmented into word unigrams, word bigrams, phoneme unigrams or phoneme bigrams, as exemplified in the following example:

Orthographic:	*zwarte drie op rode vier* (black three on red four)
Word unigrams:	/zwArt@/ /dri/ /Op/ /roj@/ /vir/
Word bigrams:	/+_zwArt@/ /zwArt@_dri/ /dri_Op/ /Op_roj@//roj@_vir/ /vir_+/
Phoneme unigrams:	/z/ /w/ /A/ /r/ /t/ /@/ /d/ /r/ /i/ /O/ /p/ /r/ /o/ /j/ /@/ /v/ /i/ /r/
Phoneme bigrams:	/+z/ /zw/ /wA/ /Ar/ /rt/ /t@/ /@d/ /dr/ /ri/ /iO/ /Op/ /pr/ /ro/ /oj/ /j@/ /@v/ /vi/ /ir/ /r+/

Note that with phoneme-based input, the word boundaries are omitted, while with word-based input, they are preserved. For the formation of bigrams, the '+' sign was used as an extra command unit at the beginning and the end of the utterance.

5.4 General setup

Each configuration, with its unique combination of parameter values and input type, was tested with the data of the first eight speakers in PATCOR. In addition, experiments were conducted with the baseline NMF decoding method, with one parameter variation: the optional use of an extra 'filler unit' column in the matrix of slot value activations. We tested the system configurations with increasing amounts of training data, resulting in learning curves. For each speaker, a separate learning curve was produced, using only that speaker's data. This setup mimics the ALADIN system in real life: the system is trained progressively on a particular user's data and adapts itself to the user's language over time as new phrases or words are introduced over time, by retraining the system at regular intervals.

A fixed test set was selected for each speaker, and the remaining data of the speaker were used for training. The original order of the utterances as they had been recorded was preserved, in order to mimic the ALADIN training situation, including possible changes in command structure over time. The test set consisted of the last 20 `movecard` utterances and the surrounding `dealcard` utterances. We constructed the test set around the number of `movecard` utterances, as accurate decoding of the `movecard` utterances is the most challenging task.

The remaining training utterances were split into partitions of 25 utterances. For each experiment, the first k partitions were used for training, with k starting at 1 and gradually increasing up to the maximum number of partitions. The command transcriptions and the automatically generated action frames were used as training input. For testing, only command transcriptions were used as input, and the output consisted of semantic frames induced by the system. The oracle frames from PATCOR were used as a reference for evaluation (cf. Table 3)

Each unique experiment, with a unique combination of parameters and the data of one single speaker, was run ten times, to account for possible performance differences due to different random system initializations (for instance at the beginning of the NMF procedure). The number of HMM training iterations (Baum-Welch) per experiment was set to twenty.

As a final evaluation experiment, we observed the best parameters and settings established during the experiments on the eight users and applied these to held-out data from an additional user for which more data is available. The results of this experiment are presented in Section 7.

5.5 Scoring

Scoring was based on a comparison between the semantic frames induced by the system and the oracle command frames in PATCOR. The used metrics are the slot precision, recall and $F_{\beta=1}$-score. These metrics are commonly used for the evaluation of frame-based systems for spoken language understanding (Wang et al., 2011). The slot $F_{\beta=1}$-score is the harmonic mean of the slot precision and the slot recall. The following formulas were used for calculation:

slot precision = # correctly filled slots / # total filled slots in induced frames
slot recall = # correctly filled slots / # total filled slots in oracle frames
slot $F_{\beta=1}$-score = 2 * slot precision * slot recall / (slot precision + slot recall)

This means that only slots that are filled with a correct value are rewarded, and both slots that are falsely filled and slots that are falsely left empty are penalized. When an induced frame is of another type than the corresponding oracle frame, the filled slots in the induced frame and in the oracle frame are consequently different, which automatically results in a relatively large drop in the slot F-score.

Various micro-averaged scores were computed, for instance micro-averaged scores across ten different runs (with different random system initializations) of the same experiment, and across experiments with different speakers' data. Computing micro-averaged scores across multiple experiments was carried out by aggregating the slot counts (i.e. number of correctly filled slots and total number of filled slots in induced frames and in oracle frames) of all the included experiments, and calculating the scores based on these accumulated slot counts, using the aforementioned formulas.

6 Results & Discussion

We first consider NMF decoding as our baseline, the experimental results of which can be found in Table 3. The best performing systems all used an extra filler unit column in the matrix V_{frames}. As expected, the scores are a lot lower than the scores with HMM decoding for most input types (Table 4), because NMF is unable to capture the temporal aspects of the commands. The scores with word bigrams, however, are a remarkable exception. Apparently, a sufficient amount of contextual information is included in the word bigrams to enable the NMF procedure to disambiguate between different slot values as accurately as the HMM decoding procedure can. NMF can also be observed to sacrifice precision for recall: this is due to the

Table 3. Top-ranked scores with NMF decoding. All scores (Prec. = slot precision, Rec. = slot recall, F = slot F-score) are micro-averaged scores.

	all	**150 training inst.**		
Command	**F**	**Prec.**	**Rec.**	**F**
phoneme uni	20.7	13.1	28.7	18.0
phoneme bi	52.9	45.4	70.8	55.3
word uni	58.5	57.3	65.5	61.2
word bi	73.6	76.6	85.6	80.8

Table 4. Top-ranked scores with HMM decoding for each input type, and the parameter values with which these top-ranked scores were produced ('non' under Fillers means non-shared fillers). All scores (Prec. = slot precision, Rec. = slot recall, F = slot F-score) are micro-averaged scores.

	all	**150 training inst.**			**Parameter Values (sharing)**			
							E	
Command	**F**	**Prec.**	**Rec.**	**F**	**Fillers**	**T**	**NMF**	**HMM**
phoneme uni	86.6	91.9	94.4	93.1	slot	+	+	+
phoneme bi	86.2	91.3	95.0	93.1	non	+	+	-
word uni	88.0	93.8	90.8	92.3	slot	+	+	+
					all			
word bi	73.0	82.1	78.5	80.3	slot	-	-	-
					all		+	

fact that during NMF decoding, multiple slot values can be activated per command unit, resulting in a relatively large number of filled slots in the induced frames.

Table 4 outlines the results of the top-performing HMM configurations per command input type. The system configurations were ranked according to their overall micro-averaged slot F-scores, which are reported in the first column of Table 4. These scores are based on the induced frames that were aggregated across all speakers, training set sizes and experiment runs (random initializations). The overall slot F-score thus takes into account the scores at all training set sizes, since the ALADIN application demands for steep learning curves, as explained in the Introduction. The next three columns of Table 4 show the micro-averaged slot scores with 150 training utterances – the largest training set size that is shared among all speakers – for the top-ranked systems. These scores were micro-averaged across all speakers and across ten experimental runs per speaker. The last four columns show the parameters of the top-performing systems. For each input type, the top row shows the parameter settings of the system with the highest overall slot F-score. Other parameter values were added (below the first row) if at least one system with that parameter value achieved an overall slot F-score that was not significantly lower than the highest score. Statistical significance of the F-score differences was tested with approximate randomization testing (as described in (Noreen, 1989)), using a critical p-value of 0.05. Only the scores of the best-performing system are reported for each input type.

When we look at the scores in Table 4, we see that the scores with word bigrams are clearly lower than the scores for the other input types. This is mainly due to data sparseness: many unknown word bigrams occur in the test data, resulting in decoding errors. The overall slot F-scores with phoneme unigrams and phoneme bigrams are very similar and are not much lower than those with word unigrams. It seems that the absence of word boundary information in the input and the smaller command unit size does not have a large impact on the slot F-scores. The slot F-scores achieved with 150 training instances are even higher with phoneme unigrams or bigrams than with word unigrams. However, we do see a difference in the balance between precision and recall: with phoneme-based command units, recall is higher than precision, whereas with word-based units, it is the other way around. The relatively high recall and low precision with phoneme-based command units can be attributed to the large number of units per command, which is likely to result in more activated slot values during decoding. The balance between precision and recall with word unigrams will be further discussed in subsection 6.2.

Looking at the parameter settings of the top-performing HMM-based systems, in Table 4, we see some differences between the optimal settings of the different input types. All top-performing systems use filler states, but the type of emission probability sharing they use for the filler states, varies somewhat. All command input types except phoneme bigrams have top-performing systems that share the filler state emission probability distributions per slot (*slot-shared*). With word-based input, sharing all filler state emissions produces practically equal results as sharing them per slot. With phoneme bigrams, on the other hand, the best results are produced with a system that does not apply any emission sharing to filler states.

Regarding the other three parameters – T-sharing and both types of E-sharing applied to slot values – there are also some differences among the input types. With phoneme or word unigrams as input, the best results are produced by systems that use all three types of sharing. With phoneme bigrams, the top-performing system uses T-sharing and E-sharing in the NMF phase, but no E-sharing in the HMM. With word bigrams, the top-ranked system uses none of the three sharing types. The effects of the different parameter settings are discussed in more detail in the following subsections. In these subsections, we will often use the abbreviated slot names (FS, FV, etc.), as specified in Fig. 5.

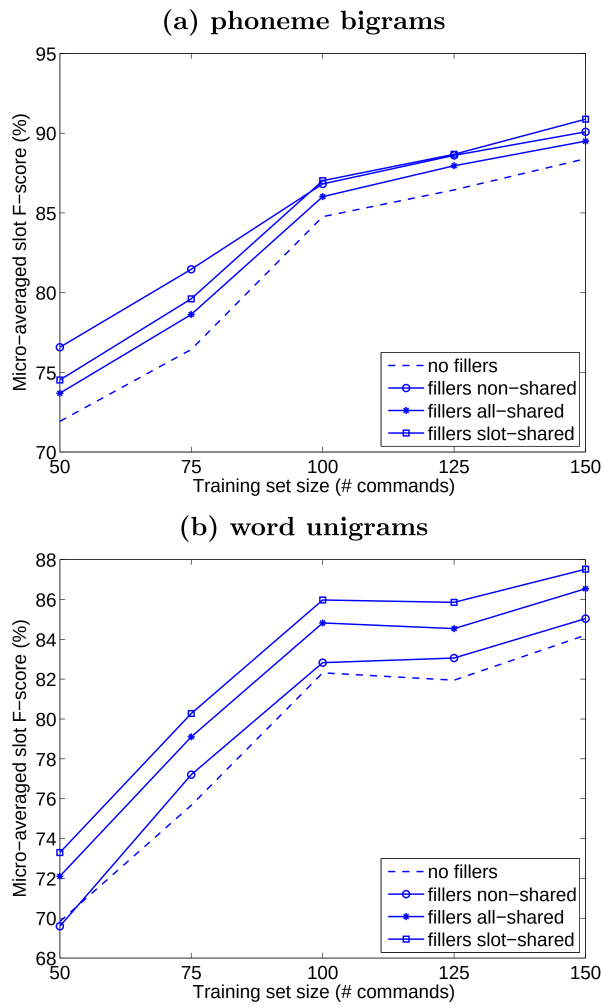


Fig. 7. The micro-averaged slot F-scores with different conditions for filler states.

6.1 Effects of system extensions

In order to compare the parameter effects, the micro-averaged slot F-scores for the different parameter values were plotted at different training set sizes. Figs 7 and 8 show the resulting graphs for two input types: phoneme bigrams, which is the input type with the highest recall, and word unigrams, which is the input type with the highest precision (cf. Table 4). The micro-averaged F-scores in the graphs were calculated based on the aggregated set of all semantic frames that were induced by systems with a specific parameter value. For instance, the broken lines in Fig. 7 show the F-scores based on all semantic frames that were induced by systems without filler states (independent of the other parameter values). The F-scores were thus micro-averaged across all speakers, all system configurations with a certain parameter value (with different combinations of other parameter values)

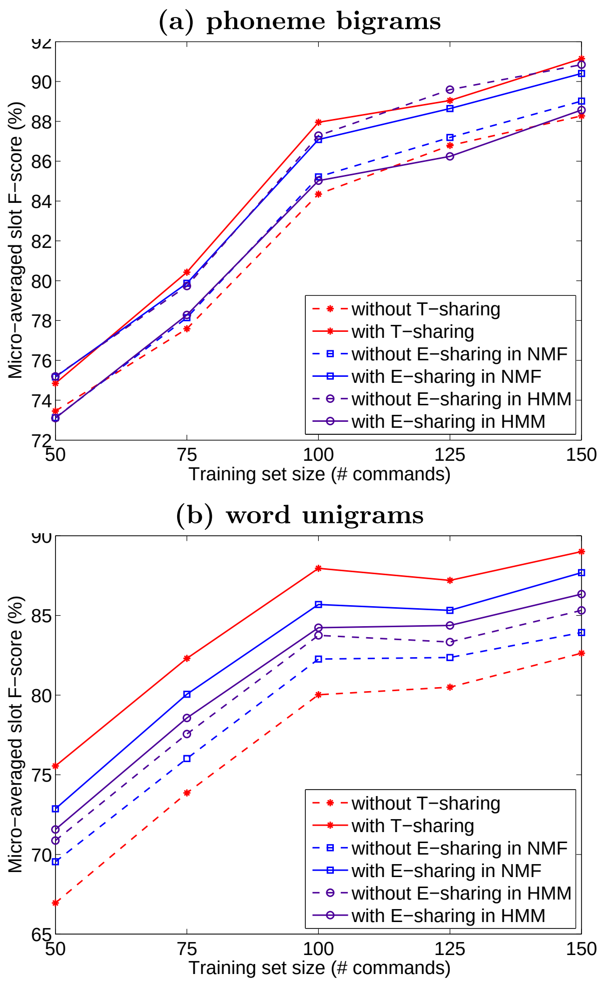


Fig. 8. The micro-averaged slot F-scores with different conditions for T-sharing, E-sharing in NMF and in the HMM.

and all ten runs per system configuration. The effects of the different parameter values will be discussed individually in the following subsections.

The top-performing filler state configurations in Fig. 7 correspond to the filler state configurations of the top-performing systems in Table 4, viz. non-shared filler states for phoneme bigrams, and slot-shared filler states for word unigrams, followed by all-shared filler states. However, in Fig. 7 we get a slightly different perspective than in Table 4. We can see that with phoneme bigrams (Fig. 7(a)), non-shared filler states produce the best results for smaller training set sizes, while for larger training set sizes, the slot-shared and non-shared filler states yield similar top-ranked scores. With word unigrams, the slot-shared filler states seem to have a consistent advantage over all-shared filler states when averaging the F-scores across all system configurations (Fig. 7(b)), while for the specific top-ranked systems in

Table 4 (with T-sharing and both types of E-sharing), the overall F-score difference between the system with slot-shared filler states and the one with all-shared filler states was not significant.

Fig. 8 affirms that T-sharing has a positive effect for both input types. With word unigrams, the effect is larger than the effects of the two types of E-sharing, while with phoneme bigrams, the effect is similar in size to the effect of E-sharing in NMF. When we look at the resulting slot value sequences, we see that they are more consistent and accurate regarding the sequential slot structures they contain, when T-sharing is used. For instance, the slot sequence "<from_suit> <from_value> <target_suit> <target_value>" that occurs in a lot of commands is more consistently present in the decodings.

In addition, Fig. 8 illustrates that the different types of E-sharing provide mixed results across input types. For both phoneme bigrams and word unigrams, E-sharing in the NMF phase has a distinctive positive effect. E-sharing in the HMM training phase, on the other hand, has a negative effect for phoneme bigrams, and its positive effect with word unigrams is relatively small.

Table 5 shows the effects of different E-sharing configurations when optimal T-sharing and filler settings are used (as defined in Table 4). Both phoneme and word unigrams benefit from E-sharing in both the NMF and HMM phase. With phoneme and word *bigrams*, however, we see different effects. With word bigrams, neither of the two E-sharing types has a positive effect, and with phoneme bigrams, E-sharing only has a substantial positive effect when it is applied in the NMF phase exclusively. We will discuss the effects of E-sharing in more detail in the qualitative inspection of the decoding output below.

The effects of T-sharing and E-sharing on individual learning curves

Fig. 9 provides some additional insight into the effect of T-sharing. It displays the learning curves of the eight speakers with word unigrams as command input for two system configurations: the top-performing system, in which slot-shared filler states, both types of E-sharing and T-sharing are used, and the same system without T-sharing. The effect of T-sharing is substantial, particularly when dealing with smaller training set sizes. For some speakers, the curves with and without T-sharing converge with larger training set sizes; for others (speakers 4, 5, 7 and 8), T-sharing keeps showing considerable positive effects on the F-scores up to the end of the curves.

Qualitative inspection of decoding output

In order to explain the effects of the different E-sharing types and the differences between them, we compared the decoding output of systems with different E-sharing settings and equal T-sharing and filler state settings. Below, we discuss these results in more detail, using decoding examples to demonstrate qualitative differences. We will focus our discussion on word unigrams and phoneme bigrams.

Inspection of the induced slot value sequences revealed that the sequences in-

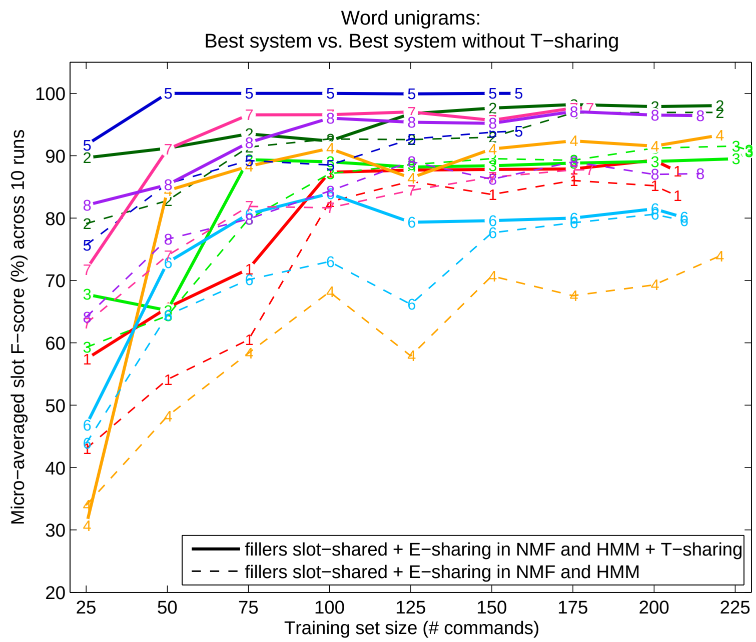


Fig. 9. Effects of T-sharing on the learning curves of the individual speakers with word unigrams as input units. The number markers on the curves are the speaker numbers. The solid curves show the scores with the best system for word unigrams (as specified in Table 4), which includes T-sharing; the broken curves show the scores with the same system without T-sharing.

duced by systems without E-sharing contain many errors pertaining to card values (the slots <`from_value`> and <`target_value`>). An example of such an error is shown in Table 6. These decoding errors result from errors in the earliest stage of the training process: the initial mapping of words to slot values by NMF. This mapping is impeded by the fact that subsequent card values typically co-occur in Patience commands (e.g. *two* → *three*, *three* → *four*), making it difficult for the frame induction engine to associate a token with the correct slot value, when only a limited number of frames and commands have been processed.

A further consequence of the ambiguous card value mappings is that the sequential command structures are not properly learned either. In other words: the errors in the initial emission probability distributions cause errors in the transition probability distributions which are learned during HMM training. When no E-sharing is used, `from` to `target` transitions are not favored over `target` to `from` transitions. In addition, the probabilities of self-transitions are strengthened due to the possibility of assigning the same slot values. This is illustrated in Table 6, where we can observe that without using E-sharing in NMF, the whole sequence is decoded as FV=2, including the word ‘three’.

Applying E-sharing in the NMF phase solves the problem of ambiguous word-to-slot-value mappings by adding extra slot values to the frame supervision. For

Table 5. The effect of E-sharing for the different input types with optimal T-sharing and filler state settings (as defined in Table 4). Columns 2 through 5 show the overall slot F-scores (micro-averaged across all speakers, training set sizes and experiment runs) with different E-sharing settings.

	E-sharing			
Input type	**none**	**NMF**	**HMM**	**NMF + HMM**
phoneme unigrams	80.05	86.05	85.50	**86.59**
phoneme bigrams	83.66	**86.23**	84.03	83.83
word unigrams	83.23	86.69	84.65	**88.01**
word bigrams	**73.01**	72.75	70.78	71.21

Table 6. The induced slot value sequences for an example sentence at training size 50 with different types of E-sharing. The first column contains the original input, i.e. the phonemic transcription of the Dutch utterance (one word per row), the second column contains the English translation in orthographic format, and the last four columns contain the slot value sequences resulting from the HMM decoding process. Decoding errors are marked in bold.

		E-sharing types			
Command		**none**	**NMF**	**HMM**	**NMF + HMM**
/d@/	*the*	filler_FV=2	filler_FV=2	filler_FV=2	filler_FV=2
/twe/	*two*	FV=2	FV=2	FV=2	FV=2
/Op/	*on*	FV=2	**TS=s**	FV=2	filler_TV=3
/d@/	*the*	FV=2	filler_TV=3	FV=2	filler_TV=3
/dri/	*three*	**FV=2**	TV=3	**FV=2**	TV=3

each `from` slot value, the corresponding `target` slot value is added to the frame supervision, and the other way around, because `from` slots and their corresponding `target` slots form shared expression sets. The column *E-sharing in NMF and HMM* in Table 6 shows that adding E-sharing in the HMM on top of E-sharing in NMF corrects the remaining errors in this example.

The fact that E-sharing in the HMM phase has a smaller positive effect on the slot F-scores with word unigrams as input type is partly due to the later stage in which sharing takes place. E-sharing in NMF can make major differences in the emission and transition probabilities, because it provides a better starting point for HMM learning, while E-sharing in the HMM can only regulate the last part of the learning process. In addition, E-sharing in the HMM phase applies expression sharing in a more subtle way than E-sharing in the NMF phase. Rather than adding extra associations between slot values and command units, the association strengths between `from` and `target` slot values and the command units that express them, are averaged amongst each other (for instance, the probabilities of the emissions FV=3 –> *three* and TV=3 –> *three* are averaged).

Table 5 shows that E-sharing has less of a positive effect with bigram input types. This can be explained by the fact that E-sharing can introduce errors in the mappings between slot values and command units when bigrams are used as input. This is illustrated by the following example, which shows the start of the command "harten acht op schoppen negen" (eight of hearts on nine of spades):

Command	**Original frame supervision**	**Additional frame supervision (E-sharing)**
/+h/	FS=h	**TS=h**
/hA/	FS=h	TS=h
/Ar/	FS=h	TS=h
/rt/	FS=h	TS=h
/t@/	FS=h	TS=h
/@A/	FV=8	TV=8
/Ax/	FV=8	TV=8
/xt/	FV=8	TV=8
/tO/	FV=8	**TV=8**
/Op/	Filler	Filler
/ps/	TS=s	**FS=s**
/sX/	TS=s	FS=s
/XO/	TS=s	FS=s
...		

In this example, the slot values in the frame supervision are aligned with the command units they are likely to be mapped to in the NMF phase when E-sharing is applied. In this case, the additional mappings, caused by the frame supervision that is added by applying E-sharing, are not all correct; see the errors marked in bold. For instance, the unit /ps/ should unequivocally express TS=s (due to the presence of the prefiller *op* in the bigram), but is here erroneously marked as FS=s as well. Such incorrect mappings typically occur with bigrams that cross word boundaries.

This can furthermore explain the E-sharing effects in Fig. 7(c). With phoneme bigrams, E-sharing in NMF still has a large positive effect because of its disambiguation of the slot value mappings, as explained previously. It also introduces some errors in the slot value mappings, but only for command units that cross word boundaries. In addition, these errors can still be corrected in the HMM training phase, if no E-sharing is applied there. When E-sharing is applied in the HMM training phase, the same type of mapping errors are introduced, but in that case, they cannot be corrected anymore. This also explains why only applying E-sharing in the NMF phase yields better scores than applying E-sharing both in the NMF phase and in the HMM training phase, as shown in Table 5.

In summary, applying E-sharing in the NMF phase yields better results than applying it in the HMM training phase, because applying it at an early stage allows it to have a relatively large positive effect, and the possible errors that it introduces – in case of bigram-based input – can still be corrected at a later stage of the learning process.

6.2 Most frequent errors with optimal settings

We analyzed the remaining errors that occurred with the optimal settings and concentrate on the most frequent errors with word unigrams as input type at 150 training utterances. As can be seen in Table 4, the recall was lower than the precision (90.78% vs. 93.84%) when word unigrams were used. The most frequent error, which had a negative effect on the recall, was that utterances such as "*aas naar boven*", in which the ace was moved to one of the foundation stacks, were often tagged as sequences of one single repeated slot value: either FV=1 or some TF value. This error occurred with almost all speakers and is due to the fact that the ace is always moved to a foundation stack and not in the playing field below.

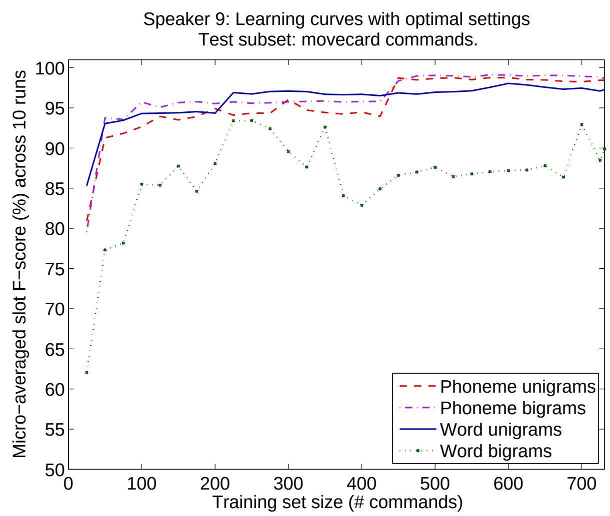
Other errors that occurred frequently are incorrectly tagged interjections such as 'uh', 'ja', etc. Sometimes these errors also percolated to other parts of the utterances. In some cases, the interjection was an unknown word, and the error could have been prevented by ignoring the word instead of mapping it onto a similar known word, as we did now. Apart from short interjections, other disfluencies such as restarts were amongst the main causes for error.

7 Evaluation experiments with optimal settings

We carried out evaluation experiments with the optimal settings that were established in the previous experiments. The optimal settings are shown in Table 4. For these experiments, we used speaker 9's data subset, which was not used in the previous experiments and is much larger than the data subsets of speakers 1 through 8. It consists of 1,142 commands and corresponding semantic frames. The last 200 `movecard` commands and the surrounding 211 `dealcard` commands were used as a test set, and the remaining commands – 440 `movecard` commands and 291 `dealcard` commands – were used for training. As in the previous experiments, the training set was divided into partitions of 25 utterances, and increasing numbers of partitions were used for training in order to produce learning curves. For word bigrams, we carried out evaluation experiments with two system configurations: the overall optimal configuration – using NMF decoding instead of using an HMM – as well as the optimal configuration with the use of an HMM (see Table 4). All experiments were carried out ten times, and micro-averaged precision, recall and F-scores were calculated in the same way as in the previous experiments.

Figure 10 shows the resulting learning curves for `movecard` commands (Fig. 10(a))

(a)



(b)

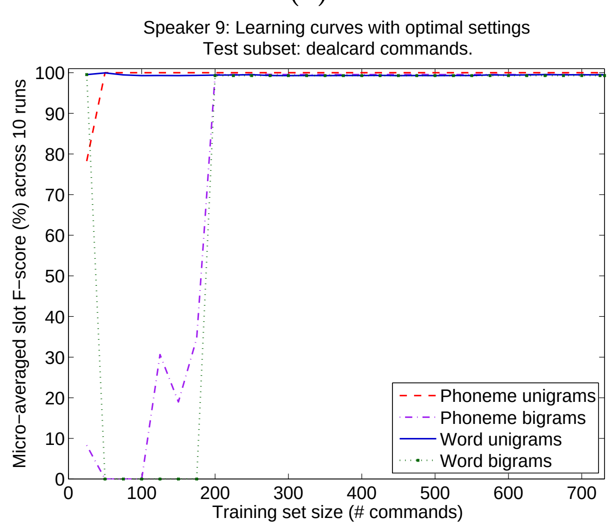


Fig. 10. Learning curves resulting from evaluation experiments with speaker 9's data, using the optimal parameter settings for each input type. The scores for the `movecard` commands are shown in graph (a); the scores for the `dealcard` commands are shown in graph (b).

and `dealcard` commands (Fig. 10(b)). With phoneme unigrams or bigrams and word unigrams, the F-scores for `movecard` commands are already between 90% and 95% with only 50 training commands (which is an average game of Patience). These curves start to level off at 100 training commands, between 94% and 95%, but the errors that are made are mainly due to the fact that the word *heer* (king), which appears quite regularly in the test set, only starts to appear in the training set after the 200th command (until then, the speaker uses the synonym *koning* instead). With word unigrams, the first appearances of *heer* in the training set directly result in a leap up to approximately 97%. With phoneme unigrams and bigrams, the leap appears later, at 450 training commands, once the word *heer* has appeared in both the `from` and the `target` position. That leap results in F-scores of around 99%, which is a bit higher than the maximum score that is reached with word unigrams (around 98%, above 500 training commands). With word bigrams, the scores are lower than with the other input types and simple NMF decoding mostly outperforms HMM decoding. This corresponds to the scores we saw in the previous experiments. Once the word *heer* starts to appear in the training data (at training size 225), the scores go up to about 93%.

In Figure 10(b), the learning curves for the `dealcard` commands are shown. With phoneme and word unigrams, the F-scores for `dealcard` commands are approximately 100% even with small training set sizes. With bigrams, however, the F-scores are lower for training set sizes below 200 commands. This is caused by the fact that in those smaller training sets, `dealcard` utterances are always "*nieuwe kaarten omdraaien*", while in many `dealcard` commands after that, the word "`nieuwe`" is omitted. In the `dealcard` commands in the test set, the word "`nieuwe`" is omitted as well.

8 Conclusion & Future Work

Our contribution to the state-of-the-art in the field of semantic frame induction, is threefold. Firstly, we presented a new application context for the task of weakly supervised semantic frame induction, viz. a speaker-dependent vocal interface geared towards physically impaired users that automatically learns a user's specific pronunciation, vocabulary and command structure from a small set of commands and associated controls. The weak supervision consists of automatically generated semantic frames, of which the slots are not aligned with segments in the commands, and which usually contain redundant information that is not expressed in the commands. Secondly, we described a framework based on NMF and HMM learning to complete this task, and some system extensions to improve its performance: HMM structure extensions and expression sharing. Unlike most SLU systems, our system directly induces frame slots *and* their values, while the HMM structure extensions keep the parameter space manageable. Thirdly, we presented a detailed analysis of the effects of the system extensions, based on textual command input (transcriptions). The used corpus is PATCOR, which contains Dutch-spoken commands in the context of a voice-controlled card game. Apart from using command input based on word unigrams, as is usually done in SLU research, we also experimented with word bigrams, phoneme unigrams and phoneme bigrams as observed command units.

In general, the results show positive effects of all the described system extensions. Sharing transition probabilities, resulting in a *hierarchical* HMM, has a considerable positive effect on the learning speed with all input types except word bigrams. The addition of filler states to deal with words that do not express slot values also shows positive effects, and the best results were produced with filler states that shared their emission probabilities slotwise. Expression sharing in the NMF phase has a positive effect for all input types except word bigrams, whereas expression sharing in the HMM phase only has positive effects with (word or phoneme) unigrams as input. The more positive effect of expression sharing in the NMF phase is mainly due to its early application in the learning process, which makes the improvement (viz. with unigram input) relatively large and enables the system to correct possible negative effects (viz. with bigram input) in a later learning stage.

Finally, evaluation experiments with the top-performing system configurations on held-out data show very encouraging learning results. With word unigrams, phoneme unigrams and phoneme bigrams as input types, scores between 90% and 95% can already be achieved with only 50 training utterances, and the main error cause was a late shift in the speaker's vocabulary. With larger training sets, in which this inconsistency was resolved, F-scores up to 98% (with word unigrams) and 99% (with phoneme unigrams and bigrams) were achieved, further underlining the system's ability to adapt to changes in language use over time.

In future research, we plan to evaluate our extended ALADIN semantic frame induction system on other datasets. The scene description task in (Roy, 2002) involves learning words and syntax on the basis of redundant sets of visual features. Similarly, the Robocup Sportscasting dataset (Chen and Mooney, 2008) contains utterances of humans commenting on simulated Robocup soccer games, coupled with (redundant) semantic descriptions of the scenes. The latter dataset has received a lot of attention with previous research efforts focusing on aligning utterances with frames (Liang et al., 2009) and learning semantic parsers (Chen and Mooney, 2008; Chen et al., 2010; Kim and Mooney, 2010; Börschinger et al., 2011). The ALADIN approach may provide an interesting addition to the state-of-the-art for this dataset, as it offers a relatively straightforward framework for semantic frame slot filling on the basis of utterances.

In the context of the ALADIN project, we will perform additional experiments in which we use the output of the frame induction engine presented in this work, as training data for a discriminative concept tagger (van de Loo et al., 2012). Experiments show that this post-processing step further improves F-scores, as this type of concept tagging is able to take more context into account during classification. Finally, we will also evaluate performance of the frame induction technique and its extensions using acoustic units as input type, as well as experiments on a home automation dataset containing both non-pathological and pathological speech.

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References

Baum, L. E. (1972). An equality and associated maximization technique in statistical estimation for probabilistic functions of markov processes. *Inequalities*, 3:1–8.

Bonneau-Maynard, H., Quignard, M., and Denis, A. (2009). Media: a semantically annotated corpus of task oriented dialogs in french. *Language Resources and Evaluation*, 43(4):329–354.

Börschinger, B., Jones, B. K., and Johnson, M. (2011). Reducing grounded learning tasks to grammatical inference. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*, pages 1416–1425. Association for Computational Linguistics.

Chang, H.-P. (1993). Speech input for dysarthric users. *The Journal of the Acoustical Society of America*, 94(3):1782–1782.

Chen, D. L., Kim, J., and Mooney, R. J. (2010). Training a multilingual sportscaster: Using perceptual context to learn language. *Journal of Artificial Intelligence Research*, 37(1):397–436.

Chen, D. L. and Mooney, R. J. (2008). Learning to sportscast: a test of grounded language acquisition. In *Proceedings of the 25th international conference on Machine learning*, pages 128–135. ACM.

Chen, D. L. and Mooney, R. J. (2011). Learning to interpret natural language navigation instructions from observations. In *Proceedings of the Twenty-Fifth AAAI Conference on Artificial Intelligence*, AAAI'11, pages 859–865. AAAI Press.

Dahl, D. A., Bates, M., Brown, M., Fisher, W., Hunicke-Smith, K., Pallett, D., Pao, C., Rudnicky, A., and Shriberg, E. (1994). Expanding the scope of the atis task: The atis-3 corpus. In *Proceedings of the Workshop on Human Language Technology*, HLT '94, pages 43–48, Stroudsburg, PA, USA. Association for Computational Linguistics.

Della Pietra, S., Epstein, M., Roukos, S., and Ward, T. (1997). Fertility models for statistical natural language understanding. In *Proceedings of the 35th Annual Meeting of the Association for Computational Linguistics*, pages 168–173.

Dempster, A. P., Laird, N. M., Rubin, D. B., et al. (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal statistical Society*, 39(1):1–38.

Dinarelli, M., Quarteroni, S., Tonelli, S., Moschitti, A., and Riccardi, G. (2009). Annotating spoken dialogs: from speech segments to dialog acts and frame semantics. In *Proceedings of the 2nd Workshop on Semantic Representation of Spoken Language*, pages 34–41. Association for Computational Linguistics.

Elffers, B., Van Bael, C., and Strik, H. (2005). Adapt: Algorithm for dynamic alignment of phonetic transcriptions. *manual available online from http://lands. let. ru. nl/literature/elffers. 2005.1. pdf*.

Epstein, M., Ward, T., Della Pietra, S., Papineni, K., and Roukos, S. (1996). Statistical natural language understanding using hidden clumpings. In *IEEE International Conference on Acoustics, Speech, and Signal Processing 1996 (ICASSP-96)*, volume 1, pages 176–179. IEEE.

Goldwasser, D. and Roth, D. (2014). Learning from natural instructions. *Mach. Learn.*, 94(2):205–232.

Hahn, S., Dinarelli, M., Raymond, C., Lefevre, F., Lehnen, P., de Mori, R., Moschitti, A., Ney, H., and Riccardi, G. (2011). Comparing stochastic approaches to spoken language understanding in multiple languages. *IEEE Transactions on Audio, Speech & Language Processing*, 19(6):1569–1583.

Hawley, M. S., Enderby, P., Green, P., Cunningham, S., Brownsell, S., Carmichael, J., Parker, M., Hatzis, A., O'Neill, P., and Palmer, R. (2007). A speech-controlled environmental control system for people with severe dysarthria. *Medical Engineering & Physics*, 5(29):586 – 593.

Hemphill, C. T., Godfrey, J. J., and Doddington, G. R. (1990). The atis spoken language systems pilot corpus. In *Proceedings of the Workshop on Speech and Natural Language*, HLT '90, pages 96–101, Stroudsburg, PA, USA. Association for Computational Linguistics.

Kim, J. and Mooney, R. J. (2010). Generative alignment and semantic parsing for learning from ambiguous supervision. In *Proceedings of the 23rd International Conference on Computational Linguistics: Posters*, pages 543–551. Association for Computational Linguistics.

Lee, D. D. and Seung, H. S. (1999). Learning the parts of objects by non-negative matrix factorization. *Nature*, 401(6755):788–791.

Liang, P., Jordan, M. I., and Klein, D. (2009). Learning semantic correspondences with less supervision. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 1 - Volume 1*, ACL '09, pages 91–99, Stroudsburg, PA, USA. Association for Computational Linguistics.

Macherey, K., Och, F. J., and Ney, H. (2001). Natural language understanding using statistical machine translation. In *INTERSPEECH*, pages 2205–2208.

Mertens, P. and Vercammen, F. (1998). Fonilex manual. Technical report, K.U.Leuven - CCL.

Mykowiecka, A., Marasek, K., Marciniak, M., Rabiega-Wisniewska, J., and Gubrynowicz, R. (2009). Annotated corpus of polish spoken dialogues. In Vetulani, Z. and Uszkoreit, H., editors, *Human Language Technology. Challenges of the Information Society*, volume 5603 of *Lecture Notes in Computer Science*, pages 50–62. Springer Berlin Heidelberg.

Noreen, E. W. (1989). *Computer intensive methods for testing hypotheses: an introduction.* Wiley, New York.

Ons, B., Gemmeke, J. F., and Van hamme, H. (2014). Fast vocabulary acquisition in an nmf-based self-learning vocal user interface. *Computer Speech & Language*, 28(4):997 – 1017.

Ons, B., Tessema, N., van de Loo, J., and Gemmeke, J. F. (2013). A self learning vocal interface for speech-impaired users. *Proceedings SLPAT 2013*, pages 1–9.

Oostdijk, N. (2000). The spoken dutch corpus. overview and first evaluation. In *Proceedings of Second International Conference on Language Resources and Evaluation (LREC)*, pages 887?–894.

Pieraccini, R., Levin, E., and Lee, C.-H. (1991). Stochastic representation of conceptual structure in the atis task. In *HLT*, pages 121–124. Morgan Kaufmann.

Roy, D. K. (2002). Learning visually grounded words and syntax for a scene description task. *Computer Speech & Language*, 16(3):353–385.

van de Loo, J., De Pauw, G., Gemmeke, J., Karsmakers, P., Van Den Broeck, B., Daelemans, W., and Van hamme, H. (2012). Towards shallow grammar induction for an adaptive assistive vocal interface: a concept tagging approach. In *Proceedings NLP4ITA*, pages 27–34.

Van hamme, H. (2008). Hac-models: a novel approach to continuous speech recognition. In *Proceedings INTERSPEECH*, pages 2554–2557.

Viterbi, A. J. (1967). Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. *Information Theory, IEEE Transactions on*, 13(2):260–269.

Wang, Y. and Acero, A. (2006). Rapid development of spoken language understanding grammars. *Speech Communication*, 48(3-4):390–416.

Wang, Y., Deng, L., and Acero, A. (2011). Semantic frame-based spoken language understanding. In Tur, G. and Mori, R. D., editors, *Spoken Language Understanding: Systems for Extracting Semantic Information from Speech*, chapter 3, pages 41–91. Wiley, West-Sussex, UK.

Zettlemoyer, L. S. and Collins, M. (2005). Learning to map sentences to logical form: Structured classification with probabilistic categorial grammars. In *Proceedings of the Twenty-First Conference on Uncertainty in Artificial Intelligence*, UAI'05, pages 658–666, Arlington, Virginia, United States. AUAI Press.