Extended HVS parser

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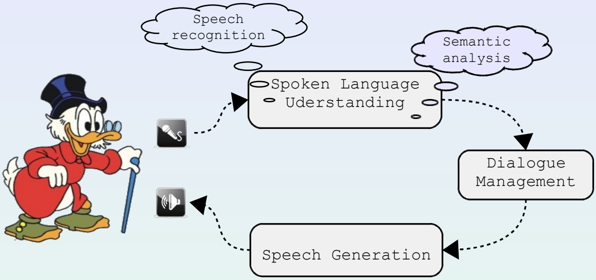
Outline

Dialogue systems



Spoken language understanding

- continuous spontaneous spoken speech
- spoken speech is often ungrammatical, includes disfluences
- the transformation into text form contains errors

Systems using ATIS data

Based on context free grammars

- TINA from Massachusetts Institute of Technology
- PHOENIX from Carnegie Mellon University
- GEMINI from SRI International

Based on statistical models

- CHRONUS (Markov models) from AT&T
- Hidden Understanding Model (HUM) from BBN Technologies
- Hidden Vector State (HVS) parser from The University of Cambridge

Concept sequence decoding

Concept sequence decoding

$$S^* = \underset{S}{\operatorname{argmax}}\, P(W|S)P(S)$$

- $P(S)$ is the semantic model
- $P(W|S)$ is the lexical model

Flat-concept parser

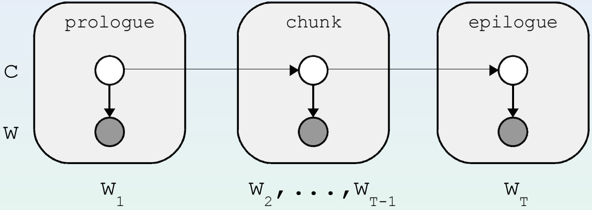


Figure: The graphical model of the FC model.

Flat-concept parser

Implementation

The semantic model is

$$P(S) = \prod_{t=1}^{T} P(c_t | c_{t-1})$$

The lexical model is

$$P(W|S) = \prod_{t=1}^{T} P(w_t | c_t)$$

The Hidden Vector State parser

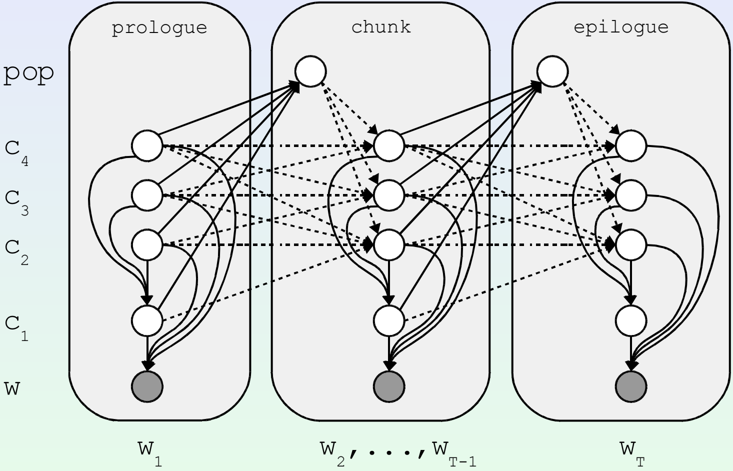


Figure: The graphical model of the HVS parser.

The Hidden Vector State parser

Implementation

The semantic model is

$$P(S) = \prod_{t=1}^{T} P(pop_t | c_{t-1}[1,4]) P(c_t[1] | c_t[2,4])$$

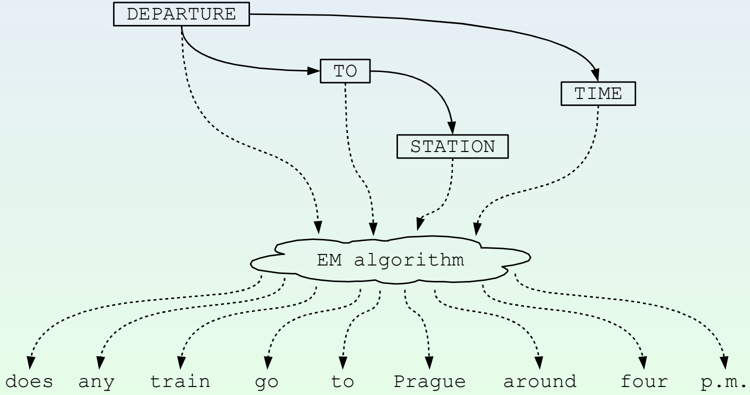
The lexical model is

$$P(W|S) = \prod_{t=1}^{T} P(w_t | c_t[1,4])$$

HVS parser - training data

Training data

does any train go to Prague around four p.m.
DEPARTURE(TO(STATION), TIME)



HVS parser - output of decoding

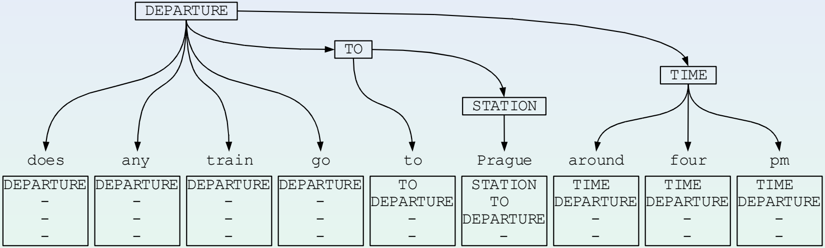


Figure: A full semantic parse tree with the corresponding stack sequence.

Outline

Semantic example dialogue - UWB

Semantics	Utterance (Literal English translation)
GREETING	the information please
GREETING	hello
DEPARTURE(TIME, TRAIN_TYPE, TO(STATION))	I have a question how can I go today by regional train to Starýho Plzence
OTHER_INFO	well we do not have many connections here
TIME, TIME	now one goes at eight sixteen if you catch it after that only at eleven ten
TIME	at eleven ten
ACCEPT(TIME, FROM(STATION))	it is not so bad at eleven ten from Hlavního yeah
TRAIN_TYPE	is it possible to take a stroller with me
ACCEPT	of course madam be sure that you can
TRAIN_TYPE	so there are the new cars

Size, cardinality and reliability

Size of the corpus

- 1,109 dialogues
- 17,900 utterances
- 2,872 unique words

Cardinality

- 35 semantic concepts (DEPARTURE, FROM, TO, STATION, . . .)

Reliability of semantics

- stability (intra-annotator's agreement): about 0.90
- reproducibility (inter-annotator's agreement): about 0.81

Difference between CU-ATIS and UWB semantic data

	CU-ATIS data	UWB data
order of semantic concepts	**not defined**	**defined**
lexical classes	defined	not defined
performance evaluation based on	extracted slot values	semantics

Order of semantic concepts

it is not so bad at eleven ten from Hlavního yeah

S1: ACCEPT(TIME, FROM(STATION))
S2: ACCEPT(FROM(STATION), TIME)

Difference between CU-ATIS and UWB semantic data

	CU-ATIS data	UWB data
order of semantic concepts	not defined	defined
lexical classes	**defined**	**not defined**
performance evaluation based on	extracted slot values	semantics

Lexical classes

it is not so bad at eleven ten from Hlavního yeah

$\Longrightarrow$

it is not so bad at eleven ten from station_name yeah

Difference between CU-ATIS and UWB semantic data

	CU-ATIS data	UWB data
order of semantic concepts	not defined	defined
lexical classes	defined	not defined
performance evaluation based on	**extracted slot values**	**semantics**

Evaluation

Frame: FLIGHT

Slots:

- FROMLOC.CITY = Boston
- TOLOC.CITY = NewYork

×

HYP: ACCEPT(TIME, FROM(STATION))

Error criteria

Semantic Accuracy - SAcc

The reference and the hypothesis annotations are considered equal only if they exactly match each other.

Example

REF: ARRIVAL(TIME, FROM(STATION))

HYP1: ARRIVAL(TIME, TO(STATION))
HYP2: DEPARTURE(TRAIN_TYPE)

Error criteria

Semantic Accuracy - SAcc

The reference and the hypothesis annotations are considered equal only if they exactly match each other.

Example

REF: ARRIVAL(TIME, FROM(STATION))

HYP1: ARRIVAL(TIME, TO(STATION))
HYP2: DEPARTURE(TRAIN_TYPE)

Error criteria

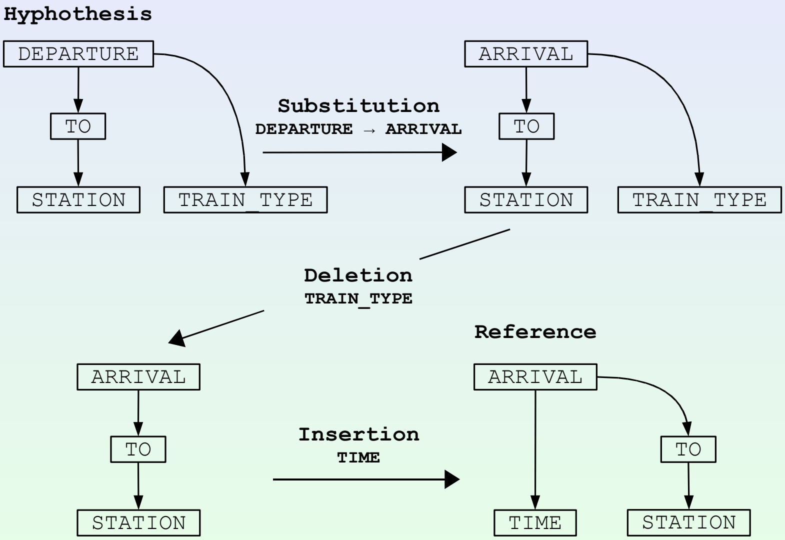
Concept Accuracy - CAcc

Measures the minimum number of:

- substitutions
- deletions
- insertions

required to transform one tree into another.

The tree edit distance



Performance

	Test data		Development data	
	SAcc	CAcc	SAcc	CAcc
the lower-bound baseline	**17.3**	**26.0**	-	-
the tuned HVS parser	47.9	63.2	50.7	64.3
the upper-bound ceiling	**85.0**	**91.0**	-	-

Tunned system

- insertion penalty
- scaling factor - $P(S)$
- pruning of vocabulary
- number of EM iterations

Performance

	Test data		Development data	
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Tunned system

- insertion penalty
- scaling factor - $P(S)$
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Outline

Positive examples

The corpus

does any train go to Prague around four p.m.	DEPARTURE(TO(STATION) TIME)
what is the price of a ticket to Cambridge around six a.m.	PRICE(TO(STATION), TIME)
if you want a direct train than it departures around nine p.m.	DEPARTURE(TRAIN_TYPE, TIME)

Positive example not labeled in the corpus (word level)

Word (words)	Concept (Semantics)
Prague	STATION
around four p.m.	TIME
Cambridge	STATION
around six a.m.	TIME
direct	TRAIN_TYPE
around nine p.m.	TIME
...	...

Positive examples

The corpus

does any train go to Prague around four p.m.	DEPARTURE(TO(STATION) TIME)
what is the price of a ticket to Cambridge around six a.m.	PRICE(TO(STATION), TIME)
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Prague	STATION
around four p.m.	TIME
Cambridge	STATION
around six a.m.	TIME
direct	TRAIN_TYPE
around nine p.m.	TIME
...	...

Negative examples

The corpus

does any train go to Prague around four p.m.	DEPARTURE(TO(STATION) TIME)
what is the price of a ticket to Cambridge around six a.m.	PRICE(TO(STATION), TIME)
if you want a direct train than it departures around nine p.m.	DEPARTURE(TRAIN_TYPE, TIME)

Negative examples not labeled in the corpus (word level)

Word (words)	Concept (Semantics)
a	STATION
around	STATION
train	STATION
p.m.	STATION
...	...

Negative examples

The corpus

does any train go to Prague around four p.m.	DEPARTURE(TO(STATION) TIME)
what is the price of a ticket to Cambridge around six a.m.	PRICE(TO(STATION), TIME)
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Negative examples not labeled in the corpus (word level)

Word (words)	Concept (Semantics)
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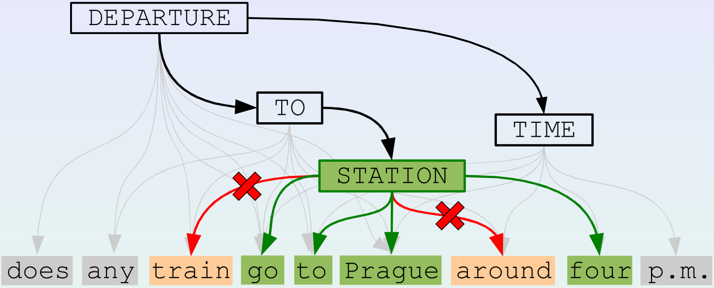
train	STATION
p.m.	STATION
...	...

Negative examples



Negative examples not labeled in the corpus (word level)

Word (words)	Concept (Semantics)
a	STATION
around	STATION
train	STATION
p.m.	STATION
...	...

Extraction of negative examples

Used concepts

AMOUNT, LENGTH, NUMBER, TIME, STATION and TRAIN_TYPE

Potential problems

- the lexical realization of the concepts AMOUNT, LENGTH, NUMBER, TIME is similar
- incorrectly annotated utterance

Utterance	Semantics
does any train go to Prague around four p.m.	DEPARTURE(TRAIN_TYPE, TIME)

- too general concept in the annotation

Word (words)	Concept (Semantics)
weather is pleasant today in Prague	OTHER_INFO
...	...

Extraction of negative examples

Used concepts

AMOUNT, LENGTH, NUMBER, TIME, STATION and TRAIN_TYPE

Potential problems

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Utterance	Semantics
does any train go to Prague around four p.m.	DEPARTURE(TRAIN_TYPE, TIME)

- too general concept in the annotation

Word (words)	Concept (Semantics)
weather is pleasant today in Prague	OTHER_INFO
...	...

Selection of proper utterances

Only utterances containing concepts

ACCEPT, ARRIVAL, DELAY, DEPARTURE, DISTANCE, DURATION, PLATFORM, PRICE, and REJECT

Example

Utterance	Semantics
what is the price of a ticket to Cambridge	PRICE(TO(STATION))
it will arrive at the second platform	ARRIVAL(PLATFORM(NUMBER))
...	...

Application of negative examples

Modification of the lexical model

$$x(w, c[1,4]) = \begin{cases} \epsilon & \text{if } (w, c[1]) \text{ is a negative example,} \\ 1/|V| & \text{otherwise} \end{cases}$$

$$P(w|c[1,4]) = \frac{x(w, c[1,4])}{\sum_{\overline{w} \in V} x(\overline{w}, c[1,4])} \quad \forall c[1,4] \quad \forall w \in V$$

where ϵ is reasonably small positive value and V is a word lexicon.

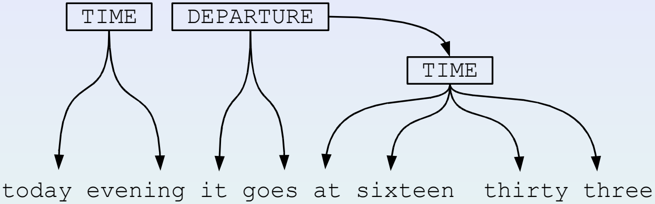
Performance

	Test data			Development data		
	SAcc	CAcc	*p*-value	SAcc	CAcc	*p*-value
baseline	47.9	63.2		50.7	64.3	
neg. examples	**50.4**	**64.9**	< 0.01	**52.8**	**67.0**	< 0.01

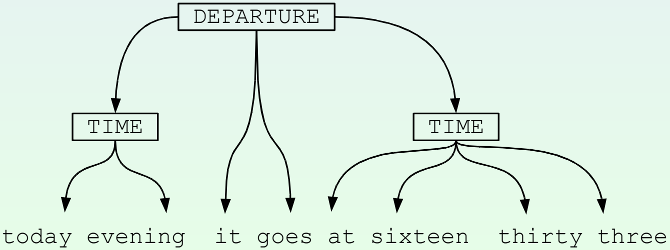
Outline

The incorrect parse tree

The incorrect parse tree from a right-branching parser



The correct parse tree from a left-right-branching parser



Recapitulation - The Hidden Vector State parser

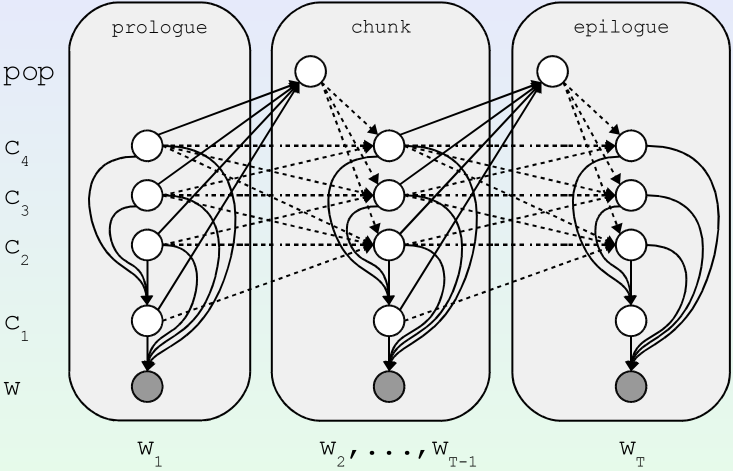


Figure: The graphical model of the HVS parser.

The HVS parser with probabilistic pushing

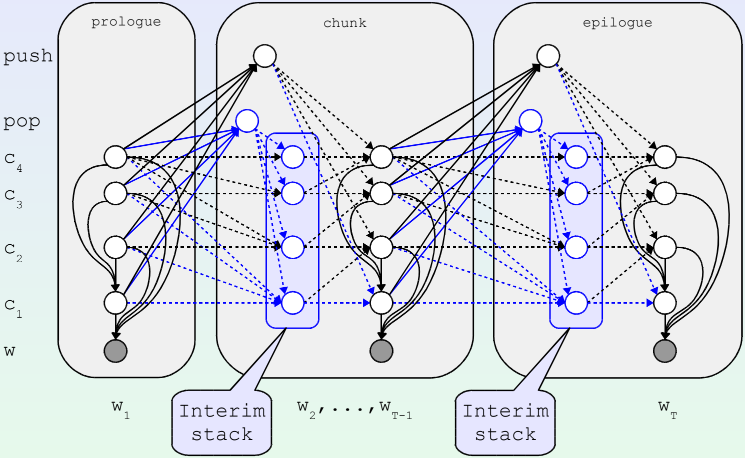


Figure: The graphical model of the HVS parser with probabilistic pushing (HVS-PP).

The left-right-branching HVS

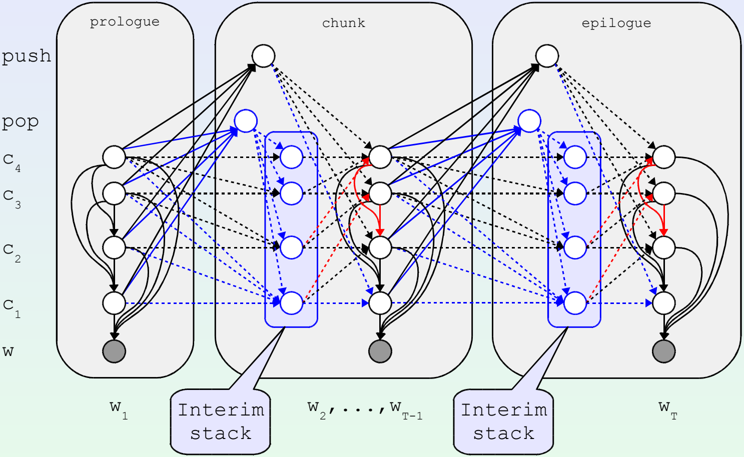


Figure: The graphical model of the right-branching HVS parser limited to insert at most two new concepts (LRB-HVS).

Mathematical representation

The HVS parser with probabilistic pushing

$$P(S) = \prod_{t=1}^{T} P(pop_t|c_{t-1}[1,4])P(push_t|c_{t-1}[1,4])$$
$$\cdot \begin{cases} 1 & \text{if } push_t = 0 \\ P(c_t[1]|c_t[2,4]) & \text{if } push_t = 1 \end{cases}$$

The left-right-branching HVS

$$P(S) = \prod_{t=1}^{T} P(pop_t|c_{t-1}[1,4])P(push_t|c_{t-1}[1,4])\cdot$$
$$\cdot \begin{cases} 1 & \text{if } push_t = 0 \\ P(c_t[1]|c_t[2,4]) & \text{if } push_t = 1 \\ P(c_t[1]|c_t[2,4])P(c_t[2]|c_t[3,4]) & \text{if } push_t = 2 \end{cases}$$

Performance

The baseline is the parser using negative examples.

	Test data			Development data		
	SAcc	CAcc	*p*-value	SAcc	CAcc	*p*-value
baseline	50.4	64.9		52.8	67.0	
HVS-PP	54.1	67.2	< 0.01	56.6	68.4	< 0.01
LRB-HVS	**58.3**	**69.3**	< 0.01	**60.1**	70.6	$<$ **0.01**

Outline

Input feature vector

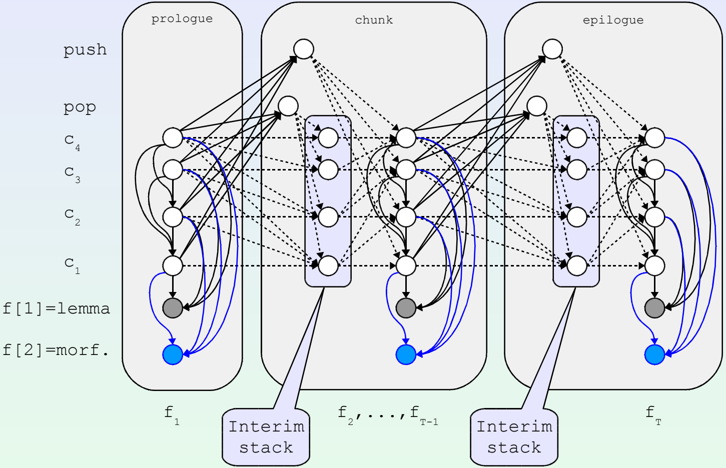


Figure: The graphical model of the HVS parser with the input feature vector composed of a lemma and a morphological tag (HVS-IFV).

Mathematical representation

Input feature vector

$$
\begin{aligned}
P(F|S) &= \prod_{t=1}^{T} P(f_t \mid c_t) \\
&= \prod_{t=1}^{T} P(f_t[1], f_t[2], \ldots f_t[N] \mid c_t) \\
&\approx \prod_{t=1}^{T} \prod_{i=1}^{N} P(f_t[i] \mid c_t)
\end{aligned}
$$

Scaling of the semantic model

$$
S^* = \arg\max_S P(F|S) P^{\lambda}(S)
$$

Performance

The baseline is the LRB-HVS parser.

	Test data			Development data		
input feature vector	SAcc	CAcc	*p*-value	SAcc	CAcc	*p*-value
baseline (Words)	58.3	69.3		60.1	70.6	
Lemmas	58.4	69.8		60.5	71.3	
Lemmas+Morphological tags	**63.1**	**73.8**	< 0.01	**65.4**	**75.7**	< 0.01

Benefits

Example

from the corpus: Words	ehm from Břeclavi to Mikulova then
from the corpus: Lemmas	ehm from Břeclav to Mikulov then
from the corpus: Morf. tags	J R N R N D
parser's input: Words	ehm from _unseen_ to _unseen_ then
parser's input: Lemmas	ehm from _unseen_ to _unseen_ then
parser's input: Morf. tags	J R N R N D
LRB-HVS Output Semantics	OTHER_INFO
HVS-IFV Output Semantics	FROM(STATION),TO(STATION)

Extra

Outline

GMTK

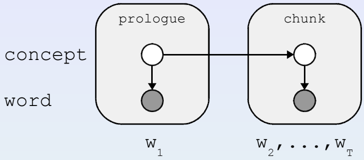
The Graphical Models Toolkit (GMTK)

- Jeff Bilmes, University of Washington, Dept. of EE
- Geoffrey Zweig, Microsoft, Speech Research Group
- `http://ssli.ee.washington.edu/~bilmes/gmtk/`
- `http://ssli.ee.washington.edu/~bilmes/gmtk/doc.pdf`

Main tools used from GMTK

- Preparing input files: gmtkTriangulate, gmtkDTindex
- Training: gmtkEMtrain(New)
- Decoding: gmtkViterbi(New)

HMM Tagger (flat-concept parser) in GMTK



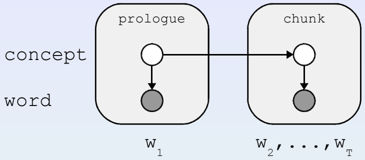

```
#include "commonParams"

frame : 0 {
  variable : concept {
    type: discrete hidden cardinality CONCEPT_CARD;
    switchingparents : nil;
    conditionalparents: nil using DeterministicCPT("conceptZero");
  }

  variable : word  {
    type: discrete observed 0:0 cardinality WORD_CARD;
    switchingparents : nil;
    conditionalparents: concept(0) using DenseCPT("wordGivenC1");
  }
}

...
```

HMM Tagger (flat-concept parser) in GMTK

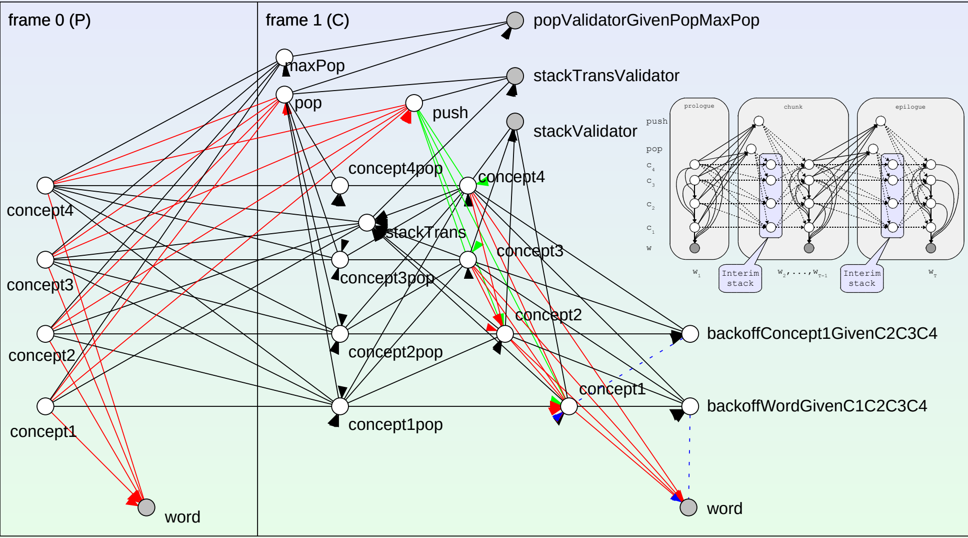



```
frame : 1 {
  variable : concept {
    type: discrete hidden cardinality CONCEPT_CARD;
    switchingparents : nil;
    conditionalparents: concept(-1) using DenseCPT("conceptGivenC_1");
  }

  variable : word  {
    type: discrete observed 0:0 cardinality WORD_CARD;
    switchingparents : nil;
    conditionalparents: concept(0) using DenseCPT("wordGivenC1");
  }
}

chunk 1:1
```

Graphical model from implementation



Stack transition validator

Motivation - Duplicit paths with the same stack sequence

$(pop_t = 1,\ push_t = 1,\ concept1_{t-1} = concept1_t)$ equals to $(pop_t = 0,\ push_t = 0)$

```
variable : stackTrans {
    type: discrete hidden cardinality STACK_TRANS_CARD;
    switchingparents: nil;
    conditionalparents: concept1(0),concept1(-1),concept2(0),concept2(-1),c
      using DeterministicCPT("stackTransGivenC1C1_1C2C2_1C3C3_1C4C4_1");
}

% make sure that in case no change on the stack, it will use pop==push==0
variable : stackTransValidator {
    type: discrete observed value 1 cardinality 2;
    switchingparents: nil;
    conditionalparents: stackTrans(0), pop(0), push(0)
      using DeterministicCPT("stackTransValidatorGivenStPopPush");
}
```

Stack transition validator - decision trees

```
1 % a DT that evaluates to one when there is "transition"
stackTransGivenC1C1_1C2C2_1C3C3_1C4C4_1
8 % number of parents
-1  {(!((p0==p1) && (p2==p3) && (p4==p5) && (p6==p7)))}

2 % a DT that validate pop, push, and stack transition
%   if there is no transition, the pop and push RV should be equal to 0
stackTransValidatorGivenStPopPush
3 % number of parents
0 2 0 default
  -1  {(p1==0)&&(p2==0)}  % the pop and push should be equal to 0
  -1  {p1||p2}    % the pop or push should be different to 0
```

Outline

Performance overview

	Test data			Development data		
	SAcc	CAcc	p-value	SAcc	CAcc	p-value
the lower-bound baseline	17.3	26.0				
original HVS parser	47.9	63.2		50.7	64.3	
negative examples	50.4	64.9	< 0.01	52.8	367.0	< 0.01
LRB-HVS	58.3	69.3	< 0.01	60.1	70.6	< 0.01
HVS-IFV	**63.1**	**73.8**	< 0.01	**65.4**	**75.7**	< 0.01
the upper-bound ceiling	85.0	91.0				

Questions?

Thank you!

And also

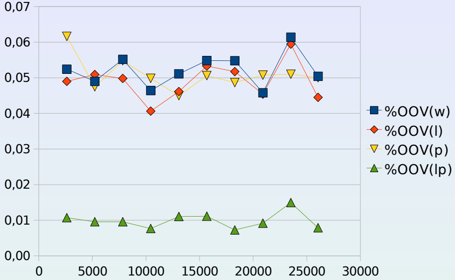
Many thanks to my colleague Jan Švec from UWB for his work on the IFV part of the parser.

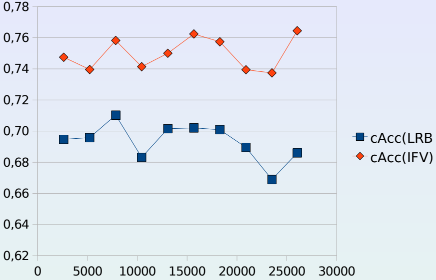
The parser is available at

http://code.google.com/p/extended-hidden-vector-state-parser/

http://code.google.com/p/dialogue-act-editor/

Original results





Sorted results according cAcc(IFV) - cAcc(LRB)