## Rapid Prototyping of Robust Language Understanding Modules for Spoken Dialogue Systems


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# Background

- In an early phase of the development of spoken dialogue systems...
  - Large amounts of data are required for robust language understanding (LU).
  - However, large amounts of data are not available.
  - **To construct robust LU modules needs a lot of efforts and is time-consuming.**



# Goal

**Rapid prototyping of LU modules**

1. Robust against various expressions.
2. Easy to construct (requires less training data).

**More robust LU modules with less training data.**



# Related Work

**Rule- or grammar-based approach**

- keyword spotting (e.g. VoiceXML)
- heuristic rules (Seneff, 1992)

☹ **Less robust against various expressions.**
- Cannot reject automatic speech recognition (ASR) errors.
- Keyword spotting does not consider grammatical rules.

☺ **Easy to construct (requires less data)**
- Preparing grammars takes less efforts.



# Related Work

**Stochastic approach**

- corpus-based (Sudoh, 2005; He, 2005)
- Weighted Finite State Transducer (WFST)-based (Potamianos, 2004; Wutiwiwatchai, 2004)

☺ **Robust against various expressions.**
- Reject ASR errors with trained LU modules.
- WFST is considering grammatical rules.

☹ **Not easy to construct (requires much data)**
- Large amount of data for training is required for robust LU.
- Collecting a large amount of data takes much effort.



# Our Approach

**WFST-based LU with simpler weightings**

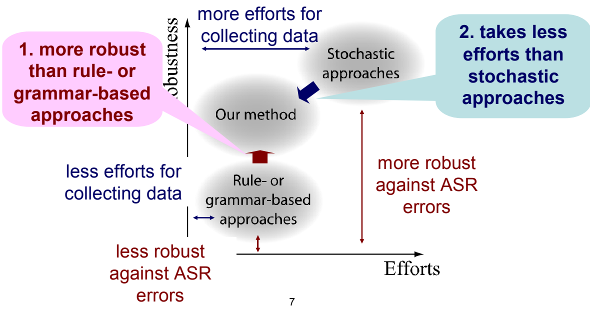
- Weighting should be simpler than conventional methods.
- Optimal parameters are obtained with small amount of data.

☺ **Robust against various expressions.**
- Reject ASR errors with trained WFST.
- WFST is considering grammatical rules.

☺ **Easy to construct (requires less data)**
- Preparing grammars takes less efforts.
- Required data for training is small.

# Position of Our Method

- A modest and realistic approach.

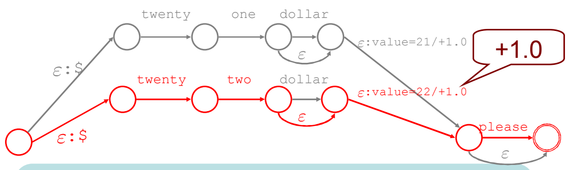





# WFST-based Approach

# WFST-based Language Understanding

- WFST accepts ASR outputs as its input.

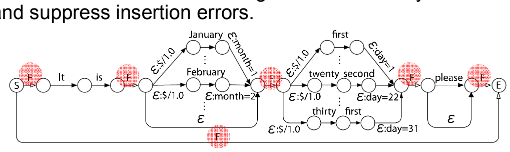



Input: twenty two, please
Output: $ twenty two value=22 please
Cumulative weight: +1.0
LU result: value=22



# FILLER Transition

- FILLER transition accepts any words.
  - FILLER transition enables to ignore unnecessary words for LU and suppress insertion errors.




* **F** represents 0 or more FILLER transitions.

Input = "It is February twenty second, please"

| LU outputs | | | | | |
|---|---|---|---|---|---|
| It | is | February | twenty | second | please |
| It | is | *FILLER* | twenty | second | please |
| It | is | *FILLER* | twenty | second | *FILLER* |
| *FILLER* | *FILLER* | *FILLER* | *FILLER* | *FILLER* | *FILLER* |



# Issue: Design of Weighting Schemes

- The path with highest cumulative weight is selected from various output sequences.

| LU output | | | | | | LU result | *w* |
|---|---|---|---|---|---|---|---|
| It | is | February | twenty | second | please | month=2, day=22 | 2.0 |
| It | is | *FILLER* | twenty | second | please | day=22 | 1.0 |
| It | is | *FILLER* | twenty | second | *FILLER* | day=22 | 1.0 |
| *FILLER* | *FILLER* | *FILLER* | *FILLER* | *FILLER* | *FILLER* | - | 1.0 |

**Requirements for weighting schemes**

1. Robust against various expressions (ASR errors).
2. Simple features for weighting.

Reduce the amount of data for training.



# Weighting Schemes for WFST

## Outline of Our Method

ASR N-best output

| | |
|---|---|
| 1 | It is … |
| 2 | Ah it is … |
| 3 | It is … |
| … | … |
| N | … |

WFST with optimal parameters

WFST output with cumulative weight

| | cumulative weight | WFST output |
|---|---|---|
| 1 | $w^1$ | … |
| 2 | $w^2$ | … |
| 3 | $w^3$ | … |
| … | … | … |
| N | $w^N$ | … |

argmax $w^i$

Language Understanding Result

training

Training data

Minimize concept error rate (CER) by changing parameters

Optimal parameters

- weighting schemes
- coefficients

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## Weighting on Two Levels

1. Weighting for ASR outputs
2. Weighting for concepts

Weighting for ASR N-best outputs

Weighting for accepted words

Weighting for concepts

$$w^i = w_s^i + \alpha_w \sum w_w + \alpha_c \sum w_c$$

$w^i$ is the cumulative weight of $i$-th sentence of ASR N-best.

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## Parameters for Training

- Five kinds of parameters to determine.

**ASR N-best** N=1 or 10?

**Accepted words** Which weighting scheme to use?

**Concept** Which weighting scheme to use?

$$w^i = w_s^i + \alpha_w \sum w_w + \alpha_c \sum w_c$$

**Coefficient** $\alpha_w$=0 or 1.0?

**Coefficient** $\alpha_c$=0 or 1.0?

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## 1. Weighing for ASR outputs
## Weighting for ASR N-Best Outputs

$$w^i = w_s^i + \alpha_w \sum w_w + \alpha_c \sum w_c$$

Reflects the reliability of the ASR output.

$$w_s^i = \frac{e^{\beta \cdot score_i}}{\sum_j e^{\beta \cdot score_j}}$$

$\beta$ is a coefficient for smoothing, $score_i$ is the log-scaled score of $i$-th ASR output.

| $i$ | $w_s^i$ |
|---|---|
| 1 | 0.78 |
| 2 | 0.10 |
| 3 | 0.09 |
| … | … |

More reliable output is assigned higher weight.

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## 1. Weighting for ASR outputs
## Weighting for Accepted Words

$$w^i = w_s^i + \alpha_w \sum w_w + \alpha_c \sum w_c$$

twenty/$w_w$

Three candidates of weighting schemes.

**1.word (const.):** $w_w=1.0$

**2.word (#phone):** $w_w=l(W)$

The normalized length of phonemes in $W$ $(0<l(W)\leq 1)$.

- Sequences with more words are simply preferred.

**3.word (CM):** $w_w=CM(W)-\theta_w$

Confidence measure for $W$ $(0<CM(W)\leq 1)$.

$\theta_w$ is the threshold for determining whether $W$ is accepted or not.

- Longer and reliable sequences are preferred.

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## 2. Weighting for Concepts

$$w^i = w_s^i + \alpha_w \sum w_w + \alpha_c \sum w_c$$

Three candidates of weighting schemes.

**1.cpt(const.):** $w_c=1.0$

value=22/$w_c$

- A preference for sequences with more concepts.

**2.cpt(avg):**

$w_c=(\Sigma_W CM(W)-\theta_c)/\#W$

**3.cpt(#pCM(avg)):**

$w_c=\Sigma_W (CM(W) l(W)-\theta_c)/\#W$

$W$: set of words in the concept
$\#W$: the number of words in $W$

- A preference for longer and reliable concepts.

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## Example: Weighting Scheme for Accepted Words

**Candidates for accepted words**

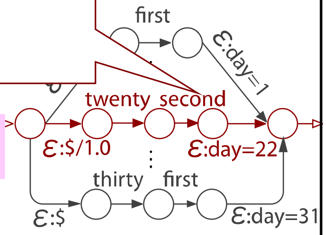
**const.** : $w_w$=1.0

**#phone** : $w_w$=0.5

**CM** : $w_w$=0.9-$\theta_w$

length of word: $l(\text{"second"})$

CM of word: $CM(\text{"second"})$






## Example: Weighting Scheme for Concepts

**average of CM**

$$\frac{CM(\text{"twenty"})+CM(\text{"second"})}{2}$$

**average of length*CM**

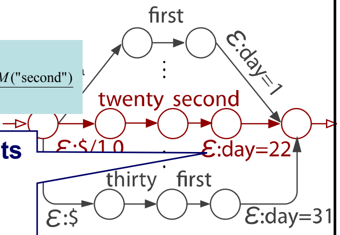
$$\frac{l(\text{"twenty"})CM(\text{"twenty"})+l(\text{"second"})CM(\text{"second"})}{2}$$

**Candidates for concepts**

**const.** : $w_c$=1.0

**avg** : $w_c$=0.95-$\theta_c$

**#pCM(avg)** : $w_c$=0.525-$\theta_c$






## Training: Determine Parameters

Training data → Minimize concept error rate (CER) by changing parameters → Determine optimal parameter sets

| $N$ | $\alpha_w$ | word | $\alpha_c$ | cpt | CER |
|---|---|---|---|---|---|
| **10** | **1.0** | **CM-0.6** | **1.0** | **#pCM(avg)-0.4** | **29.2** |
| 1 | 1.0 | const. | 1.0 | avg | 32.6 |
| 10 | 1.0 | CM-0.4 | 0 | - | 36.8 |
| … | … | … | … | … | … |

Optimal parameters

ASR N-best N=10

Accepted words word(CM)-0.6

Concept #pCM(avg)-0.4

$$w^i = w_s^i + \alpha_w \sum w_w + \alpha_c \sum w_c$$

Coefficient $\alpha_w$=1.0

Coefficient $\alpha_c$=1.0



## Cumulative Weight

ASR N-best N=10

Accepted words word(CM)-0.6

Concept cpt(#pCM(avg))-0.4

Cumulative weight $w^i = w_s^i + 1.0(4.1-5\cdot 0.6) + 1.0(1.335-2\cdot 0.4)$

Coefficient $\alpha_w$=1.0

Coefficient $\alpha_c$=1.0

| | | | | | | |
|---|---|---|---|---|---|---|
| ASR output | No, | it | is | February | twenty | second |
| WFST output | *FILLER* | it | is | February | twenty | second |
| Concept | - | - | | month=2 | day=22 | |
| $CM(W)$ | 0.3 | 0.7 | 0.6 | 0.9 | 1.0 | 0.9 |
| $l(W)$ | 0.3 | 0.2 | 0.2 | 0.9 | 0.6 | 0.5 |
| $w_w$ | - | 0.7-0.6 | 0.6-0.6 | 0.9-0.6 | 1.0-0.6 | 0.9-0.6 |
| $w_c$ | - | - | | 0.81-0.4 | 0.525-0.4 | |



# Experiments and Evaluation

## Experimental Conditions

**Two different domains**

| | Video | Rent-a-car |
|---|---|---|
| Vocabulary size | 209 | 891 |
| Example sentences | 10000 | 40000 |
| # utterance | 4186 (25 x 8sessions) | 3364 (23 x 8sessions) |
| ASR Acc. | 83.9% | 65.7% |

- Rent-a-car is more complicated domain.
  - Larger vocabulary size
  - Lower ASR accuracy

# Experimental Conditions

- We evaluated the results with 4-fold cross validation.
  - Compared concept error rate (CER).
- Two baseline methods: simple keyword spotting
  1. **Grammar & spotting:** Grammar-based ASR + keyword spotting
  2. **SLM & spotting:** Statistical language model-based ASR + keyword spotting
  - Takes as many concepts as possible without considering grammatical rules.
  - Assuming a condition that a large amount of data is not available.

Example of keyword spotting in rent-a-car domain

| | | | | | | |
|---|---|---|---|---|---|---|
| ASR Output | From | June | third | uhm | FIT | please |

➡ month=6, day=3, car=FIT ('FIT' is the name of a car)



# Result 1
# Obtained Optimal Parameters

- The optimal parameters depend on the domain.
  - Complexity of domains reflects the parameters.

| Domain | $N$ | $\alpha_w$ | word | $\alpha_c$ | cpt |
|---|---|---|---|---|---|
| Video | 1 | 1.0 | **const.** | 0 | n/a |
| Rent-a-car | 10 | 1.0 | **CM-0.0** | 1.0 | **#pCM(avg)-0.8** |

- Recognition results are not reliable in rent-a-car domain.
  - Rent-a-car domain uses ASR 10-best output.
  - Rent-a-car domain uses confidence measure for weightings.



# Result 2
# Performance of WFST-based LU

**Lower CER with our method**

- Better performance with "SLM & spotting" than "Grammar & spotting" because of robust ASR.
- Further improvement with optimal weightings for WFST.

| Domain | Grammar & spotting | SLM & spotting | Our method |
|---|---|---|---|
| Video | 22.1 | 16.9 | 13.5 |
| Rent-a-car | 51.1 | 28.9 | 22.0 |

**due to SLM-based ASR** — **due to optimal weightings for WFST**

➡ **Our method outperformed two kinds of baseline.**

➡ **More robust than keyword spotting**

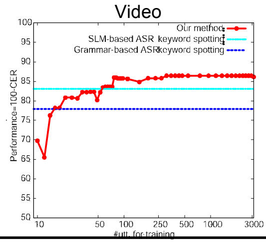


# Result 3
# Performance and Training Data

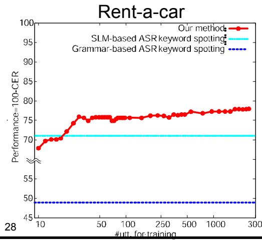
Our method outperformed baseline methods with **about 100 utterances.**

➡ **Easier to construct than stochastic methods.**
Conventional methods require several thousands of utterances.

Video




Rent-a-car






# Conclusion

**Rapidly prototyping robust LU modules.**

- WFST-based LU with simpler weighting.
- More robust than rule- or grammar-based methods.
- Easier to construct than stochastic methods.

**Experiments and Evaluation**

- Our method outperformed baseline methods with optimal weightings for WFST.
- Our method outperformed baseline methods with less utterances.
  - Conventional methods required several thousands of utterances.



# Future Work

- When to switch to stochastic approaches?
  - Stochastic approaches are more robust than our method if using large amounts of data.
  - How many data are needed for stochastic approach?