Learning Multimodal Clarification Strategies

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http://www.talk-project.org/
Example of a Multimodal Clarification Strategy

User: Show me all songs with the title “Believe”.

Wizard: I am searching for titles called “Believe”.

User: OK.

Wizard: There are too many hints. Do you know the name of the artist or the album?

User: No. Please show me a selection.

Wizard: I’m searching for a selection of this title.

User: Yes. All right.

Wizard: Should I display all albums from 2004 containing this title?

User: Yes. All right.

Wizard: I’m showing you the list.

User: OK. . . . [clicks] Show me the song from the selected album. Play it.
Why Multimodality?

Multimodality helps to reduce:

- interpretation uncertainty (Orviatt, 2002)
- the cognitive load of the user (Oriviatt et al., 2004)

The use of multimodality is context dependent:

- safety in the in-car domain
- high number of hints in the database vs. short term memory
- type of interpretation uncertainty
- user model
- etc.
Outline

Framework
Bootstrapping Reinforcement Learning from WOZ Data

Predicting Multimodal Clarification
The Data
Context/Information-State Features
Feature Engineering
Learning Experiments

Summary & Future work
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Thesis Goals

Overall goal:

*We want to learn a clarification strategy which is more natural, context dependent, and flexible, while maximising user satisfaction.*

Sub-goals

1. Investigate human behaviour given understanding uncertainties.
   → Collect data on possible strategies in WOZ experiment.
2. Learn a strategy that reflects human behaviour depending on the context.
   → “Bootstrap" an initial policy using SL.
3. Optimise that strategy for user satisfaction using RL.
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Questions to answer for generating multimodal clarification requests (CRs)

First, the DM needs to decide that “there is evidence of miscommunication” (Gabsdil, 2004). Then, we need to do generation:

1. **Content Selection and Organisation**
   - What level of (mis-) communication to address?
   - What severity to indicate?

2. **Multimodal Output Planning:**
   - Uni- or multimodal generation?

3. Realisation
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Summary & Future work
Data Collection: Introducing uncertainties

Several matches in data base

audio data

audio data

Word deletion

Synthesized audio data

Text

No visual contact graphics

also see (Skantze, ITRW 03), (Stuttle, ICSLP 04)
The Data

- 24 subjects
- 6 wizards
- 70 dialogues, 1772 turns (774 wizard turns), 17076 words
- 152 Clarification Requests (19.6%)
- 39.5 % multimodal Clarification Requests

→ Can we learn when to generate a **multimodal** CR in context? (graphic-yes vs. graphic-no)
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Local features

- DBmatches: data base matches (numeric)
- deletion: deletion rate (numeric)
- source: problem source (5-valued)
- userSpeechAct: user speech act (3-valued)
- templateGenerated: template generated (binary)
- delay: delay of user reply (numeric)
Dialogue History Features

- CRhist: number of CRs (numeric)
- screenHist: number screen outputs (numeric)
- delHist: average corruption rate (numeric)
- dialogueDuration: dialogue duration (numeric)
- refHist: number of verbal user references to screen output (numeric)
- clickHist: number of click events (numeric)
User model features

- **clickUser**: average number of clicks (numeric)
- **refUser**: average number of verbal references (numeric)
- **delUser**: average corruption rate for that user (numeric)
- **screenUser**: average number of screens shown to that user (numeric)
- **CRUser**: average number of CRs asked to user (numeric)
- **driving**: user driving (binary)
Discussion

So far:

- Binary classification task: graphic—yes vs. graphic—no
- 152 training instances
- 19 features, some numeric

How to avoid data sparseness?
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Summary & Future work
Discretisation Methods

“Global discretisation methods divide all continuous features into a smaller number of distinct ranges.”

- Unsupervised proportional k-interval discretisation (PKI).
- Supervised/Entropy-based discretisation method based on the Minimal Description Length (MDL) principle.
Feature Selection Methods

"Feature selection refers to the problem of selecting an optimum subset of features that are most predictive of a given outcome."

Searching the feature space:
- **forward selection**
- backward elimination

Selecting the features:
- Filters:
  - Other ML techniques: J4.8
  - Correlation-based subset evaluation: CFS
  - Correlation-based ranking with cut-off
- Wrappers: Selective Bayes
- Self constructed: Subset overlap
Feature selection on PKI-discretised data (left) and on MDL-discretised data (right)
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Machine Learners

Baseline:
- Majority baseline (graphic-no): **45.6 %** weighted f-score
- 1-rule baseline: **59.8 %** weighted f-score

Machine Learners:
- Rule Induction: RIPPER
- Decision Trees: J4.8
- Naïve Bayes
- Bayesian Network
- Maximum Entropy
### Results

<table>
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<tr>
<th>Feature transformation/ w. f-score (%)</th>
<th>1-rule baseline</th>
<th>Rule Induction</th>
<th>Decision Tree</th>
<th>maxEnt</th>
<th>NB</th>
<th>Bnet</th>
<th>Average</th>
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<tr>
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<td>76.1</td>
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Conclusions

Only the “right” combination of ML model, discretisation method, and feature selection algorithm shows a significant improvement over the 1-rule baseline.

- best performing combinations: Bayesian models with wrapper methods (w. f-score of 84.1%, 58% reduction in error rate)
- MDL discretisation better than PKI.
- ‘vertical’ differences bigger than ‘horizontal’
- best performing feature selection method: subset overlap
- best performing feature subset: `templateGenerated`, `screenHist`, `screenUser`
Discussion: Best performing feature subset

Predictive features:

+ templateGenerated
+ screenHist
+ screenUser

→ Other studies (using RL for feature selection) found *repeated concept* to be important

Less predictive features:

- refUser
- deletion
- DBmatches
- source

→ These (local) features might contribute for a larger data set!
Summary

• Framework: “Bootstrap” a RL-based system
• Data collection in a WoZ study.
• Initial strategy learning for when to generate multimodal CRs: 84.1% w. f-score (24.4% improvement over 1-rule baseline)
• Feature engineering as essential step using a large feature space with little data to achieve significant performance gains
• Wizards’ behaviour is learnable but is considered to be sub-optimal.
Future work

(Near) future work: Richer annotations

- Add reward level annotations for RL.
- Estimate transition probabilities for MDP for other action decisions (e.g. severity, grounding level).

(Distant) future work:

- Evaluate learnt policy against a hand written strategy.
- Test the portability to other domains.
Papers associated with this talk:

Weighted f-score

“F-score which says something about recall and precision w.r.t. class frequencies in the data.”

\[ \text{wf} = \sum_{i=1}^{\mid C \mid} w_i f(C_i) \]

• Weight the f-score of each class by the class frequency in the data;
• Create the sum.
Rich Data Annotation

• **Features**: Annotation standards for multimodal dialogue context: Joint TALK/AMI workshop, Dec 12th 2005
  
  http://homepages.inf.ed.ac.uk/olemon/standards-workshop-cfp2.html

• **Method**: NXT format and the NITE XML toolkit (Carletta, 2005)
Appendix

NXT Format
Appendix

NITE toolkit reference coder
Appendix

NITE toolkit gesture coder
Appendix

NITE toolkit dialogue act coder
The End

Thank you for your attention!