Introducing Ratatouille: a Generalizable Goal-Oriented Dialog Bot

Team M. Amram – J. Toledano
Faculty N. G. des Mesnards – T. Zaman
Company L. Gerdes – R. Sehgal – I. Pyzow

Problem Statement
Commercial solutions use human workforce to frame dialog with rules

Domain knowledge
- Expertise required to formulate business use case
- Conversation transcripts
  - Sample dialogs required to scope bot features

Business analysts
- Business analysts can be retrieved from base dialog flows
- Formulate a base dialog flow for a given use case
- Handcraft a specific series of rules from base dialog flows

Rule-based dialog flow
- Bot leads conversation using preset question-flow based
- Bot classifies user responses using its handcrafted rules

Examples
- Type constraint
- Vertical
- General literature
  - Informative DB
  - Structured knowledge
    - Database of structured information required to answer user requests
  - Extensive conversational data
    - Thousands of labeled conversation transcripts required to use deep learning

Our solution leverages deep learning to improve generalizability

Deep architecture
- Deep learning algorithms infer patterns from textual data to frame any dialog

Generalizable model
- Can be extended by:
  - Switching database
  - Incorporating new features by generating new conversations
  - Curating transcripts for any business use case

Data Integration & Architecture
Two enhanced sources fuel the restaurant recommendation task

Structured Database
- Information about 1,000 restaurants in Boston, Cambridge, and Waltham
- Data collected using APIs from Yelp, Zomato, and OpenTable
- Set of scripts automates data integration and cleaning

Transcripts
- More than 3,000 open-source conversation transcripts published by University of Cambridge
- Augmented with new features and automatically generated sentences by bespoke parsers

Our end-to-end architecture predicts the bot’s next response

Natural Language Understanding
- Dialog Management
- Natural Language Generation

Demonstration Application
Bot takes into account food type and neighborhood constraints
- More details, such as the address, can be requested
- User can switch between cities within a conversation
- A picture can be requested by the user
- Bot understands city switch and inquiries about new preferred area

Project Timeline

February
- General literature review
March
- End-to-end architectures
April
- Building Informative DB
May
- Implementing Bot modules

On-campus research
June
- Release of Alpha version
July
- Example level generalizability
August
- Feature level generalizability

On-site internship

Impact
Customer acquisition
- Display advanced capabilities to prospective customers
- Meet customer expectations
- Adapt rapidly to new customer use cases

Churn reduction
- Act on customer preferences
- Automate customer satisfaction analysis
- Answer questions with high accuracy 24/7

Cost reduction
- Automate repetitive tasks
- Allow exceptional people to focus on high-value problem solving
- Scale up and down depending on customer requirements

Examples
Vertical
- User-friendly solutions bring about massive adoption
- Brands use bots to retain tech-savvy customers

Path Forward
New Use Case
- Methodology to apply the architecture to a new business use case:
  - Gather and curate thousands of conversation transcripts
  - Build the corresponding informative database by scraping the web
  - Train the core deep learning modules

Algorithm
- Promising research-stage architectural developments:
  - Memory Networks: RNN that selects and stores relevant dialog chunks in memory
  - Frames Tracking: adding a memory module to rewind the dialog
  - Reinforcement Learning: takes into account the future turns of the conversation to optimize the local dialog state

Infrastructure
- From a prototype to production-ready solution:
  - Training the core RNN with GPU reduces training time from 7 hours to 30 minutes
  - Cloud hosting allows the bot to communicate with several users simultaneously to improve scalability