Reference Resolution and Context Change in Multimodal Situated Dialogue for Exploring Data Visualizations

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Abstract

Reference resolution, which aims to identify entities being referred to by a speaker, is more complex in real world settings: new referents may be created by processes the agents engage in and/or be salient only because they belong to the shared physical setting. Our focus is on resolving references to visualizations on a large screen display in multimodal dialogue; crucially, reference resolution is directly involved in the process of creating new visualizations. We describe our annotations for user references to visualizations appearing on a large screen via language and hand gesture and also new entity establishment, which results from executing the user request to create a new visualization. We also describe our reference resolution pipeline which relies on an information-state architecture to maintain dialogue context. We report results on detecting and resolving references, effectiveness of contextual information on the model, and under-specified requests for creating visualizations. We also experiment with conventional CRF and deep learning / transformer models (BiLSTM-CRF and BERT-CRF) for tagging references in user utterance text. Our results show that transfer learning significantly boost performance of the deep learning methods, although CRF still out-performs them, suggesting that conventional methods may generalize better for low resource data.

1 Introduction

Conversation is understood in context. When the world, whether real or simulated, can change because of the processes that change the world itself; in this context, reference resolution, which is tasked with linking what the user refers to with objects in the world, is crucial for a dialogue system to effectively respond to the user, including to create the new entities themselves.

In this work, we discuss our approach to new entity establishment and reference resolution to deal with references to visualizations on a large screen display where new visualizations are constantly being added and then moved, opened/closed, or even removed. In our CITY-CRIME-VIZ corpus, (see Section 3), the user may ask $U_1$: can I see theft in the downtown area, resulting in a first visualization $Viz_1$; and then $U_2$: can you show that graph by day of the week?, which results in a second visualization $Viz_2$. $Viz_2$ is created by first resolving the referring expression that graph to $Viz_1$, and then generating the specifications for $Viz_2$ by updating the specifications for $Viz_1$ according to $U_2$. This is an example of accommodating context change, a notion first introduced by (Webber and Baldwin, 1992) in their discussion of new entities that are the results of physical processes as in cooking: Mix the flour, butter and water. Knead the dough until smooth and shiny. In the 30 years since (Webber and Baldwin, 1992), not much work has been done on how to accommodate the creation of new entities (see (Wilson et al., 2016) for documents and (Li and Boyer, 2016) for tutoring dialogues about programming), and none in the visualization domain; and none that marries traditional information-state architecture with contemporary lexical representations and approaches as we do here. Additionally, our task is inherently multimodal, specifically as concerns deictic gestures.

Our overall research goal is to build a conversational assistant to support users explore data visualization via multimodal interaction. We collected a corpus of interactions City-Crime-Vis from 16 sub-
jects tasked with forming effective police deployment strategies based on crime patterns discovered while exploring visualizations of our city’s public data. The subjects interacted with a Visualization Expert (VE) which they knew to be a person interacting remotely from a separate room. We have designed, developed and evaluated a first version of our assistant (References withheld); the reference resolution work we describe here is part of a second version of the assistant.

We highlight our contributions as follows. (1) We believe we are the first to code for visualization references in a large screen environment supporting multiple visualizations at a time. We tagged referring noun phrases (NPs), data attributes (slot fillers) in these NPs, and co-occurring pointing gestures. Because the user rarely fully specifies the visualization to be created, we can use the slot fillers as components of semantic structures that are used both to find the referent visualization, and to create the specification for the new one. (2) Existing visualization software have applied rule-based grammars for detecting references in text, which are difficult to scale, including to the different forms these references can take (pronouns, deictics, full NPs). Alternatively, we use conditional random field (CRF) to detect referential expressions, achieving an F1 score of 61.6% on our corpus data. (3) Furthermore, we investigated several deep learning (DL) models for reference detection. Given the small size of our data, we found that using transfer learning techniques leads to an increase in F1 score by 10% over the single task learning baselines. However our experiments also show that our CRF tagger attains superior performance. This is noteworthy as it shows that conventional methods may be better suited for certain tasks and domains for which scarce data is available. (4) Lastly, our reference resolution model crucially relies on an information-state architecture (Larsson and Traum, 2000). It constantly updates the dialogue state after each conversational turn, to keep track of the visualizations on the screen at that instant and information about each of them. Additionally, while our model encodes preference towards more recently added visualizations to the screen, dialogue state allows access to all those currently visible. This approach boosts accuracy by 6% over the baseline, in which only the most recent visualization is an eligible candidate referent.

We strongly believe in ecologically valid data, which in our case is multimodal as well. This data is by nature small, in fact tiny as compared to most current datasets. We believe work like ours complements work conducted on large datasets such as Multiwoz (Budzianowski et al., 2018), which are somewhat artificially generated.

2 Related Work

Multimodal Dialogue Corpora. Efforts to build corpora with referential cues in situated multimodal dialogue are not new (e.g., referential annotations based on speech and eye gaze for puzzle pieces (Iida et al., 2011); speech and haptic gestures for human-robot interaction (Chen and Di Eugenio, 2012; Chen et al., 2015), and so on). Specifically for visualization, Quda (Fu et al., 2020) includes task annotations for independent queries, but no dialogue corpus is available that we are aware of.

Multimodal Reference Resolution. When processes take place in a real or simulated world, then the user refers to objects not only through language, but also through nonverbal cues such as gestures (Navarretta, 2011; Qu and Chai, 2008; Landragin, 2006; Eisenstein and Davis, 2006), eye gaze (Prasov and Chai, 2008; Iida et al., 2011; Kim et al., 2017), and haptic information (Foster et al., 2008; Chen et al., 2015). The objects being referred to could be text entities introduced earlier in the discourse or those in external environments, such as icons on a screen (Kehler, 2000), ingredients or tools for a recipe (Whitney et al., 2016; Chen and Di Eugenio, 2012).

Reference Resolution applied to Visualization. Other visualization systems either limit interaction to system-initiative dialogue flow (Cox et al., 2001), only handle referents to objects within the current visualization (Sun et al., 2010; Gao et al., 2015; Narechania et al., 2020), or only track referents for follow-up queries on a current visualization (Reithinger et al., 2005; Setlur et al., 2016; Hoque et al., 2017; Srinivasan and Stasko, 2017). Similar to our work, Flowsense (Yu and Silva, 2019) and Articulate (Sun et al., 2010) are capable of displaying multiple visualizations to the user as well. However in contrast to these applications, we focus on reference resolution within a dynamic environment (Webber and Baldwin, 1992) in which each new visualization introduced into discourse is constructed at that time and can subsequently be moved or removed from the screen at a later time. Furthermore, we are the first (as far as we know) to
Transfer Learning techniques are known to boost deep learning performance in low resource settings such as ours. Transfer learning gives a model new insight from auxiliary tasks rather than training from scratch on the target task, consequently reducing training time and improving generalization on smaller data (Pan and Yang, 2009).

It is a vital tool for NLP due to data scarcity for domain focused language data, gaining considerable popularity especially for contextual embeddings (Rahman et al., 2020; Howard and Ruder, 2018; Radford et al., 2018), speech recognition (Song et al., 2019), sequence tagging (Perl et al., 2020; Søgaard and Goldberg, 2016), and user adaptation (Genevay and Laroche, 2016).

3 Dataset and annotations

Our City-Crime-Vis corpus comprises multimodal interaction for 16 subjects that explored public crime data in our city to better deploy police officers. As noted, they spoke with a human VE who remotely created visualizations on a large screen, was not visible and did not speak back. The corpus contains 3.2K utterances. Since the user was encouraged to reason out loud about the patterns discovered via visualization, conversational turns often start with think aloud, followed by what we called an actionable request (AR) for the VE.

Using ANVIL (Kipp, 2001, 2014), we annotated 449 utterances in context as ARs, hence obtaining 449 CARs (contextual actionable requests): a CAR consists of setup, i.e. think aloud prior to the AR (up to and including utterances that mention data attributes, if any); the AR; and the conclusion, the think aloud subsequent to the AR (also based on data-attribute mentions). Figure 1 illustrates an excerpt from the corpus, comprising two CARs.

Each AR is annotated for user intent with one of 8 Dialogue Acts (DA) labels, e.g., WINMGMT for window management operations, such as closing, moving, maximizing, or minimizing a visualization; CREATEVIS for creating a new visualization from scratch; MODIFYVIS for creating a new visualization based on an existing one. Referential expression annotation is described next. Full details on the annotation, including intercoder agreement, can be found in (Reference withheld). The transcribed corpus is publicly available; and so is an augmented dataset built to alleviate data scarcity, comprising a 10-fold increase to 160 subjects covering approximately 15K utterances obtained via delexicalization and paraphrasing.

3.1 Referring Expressions

We annotated both text (NPs) and gestural references to visualizations. Hand gestures were coded with various labels (e.g., the kind of gesture, the objects pointed to on the screen, and so on); approximately a third were identified as referential when they co-occur with text references. Within text references, we also identify certain phrases as slot fillers corresponding to data attributes (i.e., slots) in our knowledge ontology (KO)\textsuperscript{1}.

We labeled a total of 294 references in the corpus (176 text references (60%) and 118 gesture references (approximately one third co-occur with text references (40%))) as well as 680 slot fillers. For reference resolution, we attained an excellent intercoder agreement of $\kappa = 0.85$ with 2 judges on the full interaction from one subject: the transcript and potential references were provided, and each of the judges filled out the referent target visualization for each reference.

Currently, for simplicity, our model focuses on single references occurring in setup and AR, not in conclusion. Consider “Can you bring up the the graph behind the River North one?” The user refers to two visualizations here: the "the River North one" and the graph placed behind it on the screen. We only evaluate “the graph” in this case since we only process a single reference per request.

We also only consider visualization references to a single target. The request “[...] I would like to see battery by– well I would like to see battery by day of week, battery by month, and battery by year.” results in 3 new corresponding visualizations. However, our model only adds one of these visualizations to the dialogue history (DH) as part of the evaluation and hence we ignore any references to either of the other two visualizations, which are not in the DH.

Table 1 presents reference counts for setup and ARs: 5% of text references are in setup and 62% in ARs; 8.5% of gesture references are in setup and 74% in ARs; hence, 33% of text references (52) and 18% of gesture references (21) appear in

\textsuperscript{1}Semi-automatically constructed via external sources comprised of 3.5K total terms categorized into 11 parent slots such as CRIME TYPE, NEIGHBORHOOD, MONTH, YEAR (Reference withheld)
Table 1: Text and gesture reference corpus counts.

| Category     | Setup | Request |
|--------------|-------|---------|
| Overall      | 19    | 109     |
| Single References | 18    | 86      |
| Single Targets    | 14    | 66      |

| Gesture References |
|-------------------|
| Total: 118        |
| Category           | Setup | Request |
| Overall            | 10    | 87      |
| Single References  | 9     | 70      |
| Single Targets     | 9     | 45      |

Conclusion. Single references account for about 94.7% of references in setup and for about 80% of those in ARs. Finally, when filtering on single targets, we are left with the 80 text and 54 gesture references on which we will focus.

4 Approach: Detection, Resolution, and New Entity Establishment

The pipeline relies on an information state architecture with dialogue state tracking. Reference resolution is carried out in two particular scenarios: the user asks to (1) perform window management on a current visualization (e.g., close, move, and so on) or (2) create a new visualization based on current data or template. An example for the latter is shown in Fig. 2, in which the user asks to construct visualization "09" by using "08-3" as a template. The pipeline begins with language understanding of the full CAR #2 from Fig. 1 (we only show the AR part of the entire CAR segment here for simplicity) to form a User Action frame containing fixed frame attributes. While user intent, visualization references, and slots are filled, others are left empty either because of under-specification by the user (e.g., axes labels, plot title, plot type, and so on) or they require back-end processing (e.g., query results to retrieve requested data, referent visualization identifiers to resolve references). Then the state tracker uses the DH to keep track of which visualizations are on the screen. In Fig. 2, the DH contains a single entry for "08-3". Subsequently, the dialogue manager executes a dialogue policy which aside from making back-end decisions such as forming an SQL query for data retrieval, also seeks to populate the unknown frame attribute values; it outputs an Agent Action frame (structurally identical to User Action). Finally the state tracker adds the Agent Action as a new entry in the DH while the system also outputs a json object (which we call a visualization specification) that instructs a separate visualization interface software to accordingly update the screen (i.e., add visualization "09" in this case).

As concerns referring expressions and their resolution, the pipeline undertakes the following steps, to be described in detail next: referring expression detection; semantic structure / visualization vector construction; reference resolution; new entity establishment.

4.1 Detection

We trained a sequence tagging model to detect text references (see Section 5.1 for details). The model predicts tags using the standard IOB2 format (i.e., "B-REF"/"I-REF"/"O-REF" for beginning of / inside / outside text reference respectively. In the current example, our model tagging output is: 

\[(Ok, O), (let's, O), (have, O), (a, O), (look, O), (can, O), (you, O), (have, O), (this, B), (graph, I), (for, O), (months, O), (of, O), (the, O), (year, O)]\].

The User Action frame (#1 in Fig. 2) attribute Text Ref. is updated accordingly.

Gestures are determined to be referential if they are pointing to a visualization on the screen and also co-occur with a text reference. In our example, a text reference is present ("this graph") hence the User Action frame boolean attribute Gest Ref. is set to True.

4.2 Semantic Structure Construction

Each time a user asks to construct a new visualization, our model looks for slots in the request to form the semantic structure for the new visualization (this also applies for the referring expression). In particular, we find phrases that are in close proximity in the embedding vector space to terms in the KO, by using a domain targeted word embedding model (WE)\(^2\). Subsequently the candidate words are pruned based on linguistic patterns using the SpaCy\(^3\) dependency parse of the entire utterance to form the finalized list of slot fillers. For example in the AR in Fig. 2, the prepositional phrase "for months of year" contains the complements "month" and "year", both of which are known as temporal slots in KO. Here, the terms are merged to form "months of year", and mapped to the parent slot MONTH, since "month" appears first in the phrase.

\(^2\)100-dimensional continuous bag-of-word model trained on 5GB of online articles and wikipedia pages related to crime.

\(^3\)http://spacy.io
The slot fillers are then transformed to low-dimensional space. In particular, the 11 slots in the KO are projected onto an embedding space along 11 dimensions, each computed using the WE model, representing features for visualization and referring expressions. In case a slot filler corresponds to a slot value in the KO, it is simply averaged into the corresponding parent slot position in the feature vector.

4.3 Reference Resolution

In Fig. 2, the DH contains only an entry for "08-3" introduced previously in the interaction. Subsequently, when resolving visualization references for future visualization "09" the model only considers "08-3" as a candidate referent (it is selected because their cosine similarity score exceeds a cut-off score).

Our model encodes preference to the most recent entries. If \( n \) represents the total entries in the DH, then the visualization vectors of the most recent \( \frac{n}{2} \) entries in the DH are associated with a multiplicative factor of 1.0 signifying that they are equally preferred. The latter \( \frac{n}{2} \) entries in the DH however are associated with a linear decrease by a factor of \( \frac{1}{n} \). For example, if \( n = 6 \), then any of the most recent 3 entries are equally likely candidates; the visualization vectors for the remaining entries are multiplied by factors of \( \frac{2}{3}, \frac{1}{3}, \) and \( \frac{0}{3} \) respectively. Finally, cosine similarity is used to score each visualization in the DH relative to the referring expression and the visualization with the highest score is selected.

4.4 New Entity Establishment

Finally visualization "09" is constructed using the "08-3" template. Note that MONTH serves a double purpose since it was used to resolve the referring expression (via WE embedding and cosine similarity among semantic structures), while also...
replacing WEEK as the temporal axis in "09".

Our model also infers missing information the user does not mention in the request. For example plot type is set to line chart in the presence of temporal entities to better display trends across time. Otherwise, by default bar chart would be selected since 56% of all visualizations in the corpus are bar charts. In the case of follow-up requests, in which the user makes reference to a visualization from a previous query, information can be added from the original request. In the running example, CRIME is added to the entities list in the Agent Action because "08-3" of the previous request includes it.

5 Experiments and Results

5.1 Detection

As described in Sec. 4.1, we treat the problem of detecting text references (DTR) as a sequence labeling task. With only 294 references appearing across 449 CARs in the corpus, the task has access to a limited number of labels for model training. We investigated transfer learning to address data insufficiency, i.e. our goal is to transfer knowledge from a source sequence tagging task with access to a large number of labels (i.e., NER in our case) to DTR. The City-Crime-Vis corpus data is supplied to the DTR task associated with 3 possible tags (see Sec. 4.1) while the augmented dataset of approximately 15K utterances (see Sec. 3) is provided to the NER task, comprising 23 labels (the "B" and "I" tag for each of the 11 parent slots in the KO plus "O" tag).

For knowledge transfer in sequence tagging problems, a generalizable architecture is preferred to optimize relatedness of tasks to maximize weight sharing (Collobert et al., 2011). Advanced approaches known to combine the benefits of CRF with deep learning (Collobert et al., 2011; Hammerton, 2003; Jagannatha and Yu, 2016; Chiu and Nichols, 2016) in particular can be leveraged where only the CRF layer needs to be adjusted to account for the difference in labels while sharing the other layers (Yang et al., 2017). For our experiments, we chose CRF for sequence tagging (Fields, 2001; Sha and Pereira, 2003) which is implemented using Sklearn-CRF Suite\(^4\) package; and also chose BiLSTM-CRF and BERT-CRF are implemented in Keras\(^5\).

5.1.1 Features

The input to the models consist of utterances (20 words maximum), coarse-grained POS tags, and sequential text features. They are trained using 5-cross validation. For training CRF we used LBFGS optimization with 0.10 coefficients for L1 and L2 regularization. BiLSTM-CRF is trained on a batch size of 1024 and 10 epochs and BERT-CRF is trained on batch size of 64 and 5 epochs. Early stopping was applied to F1 score to address class imbalance. Finally, "O" tags which commonly dominate other labels in NER data are addressed by skipping utterances only containing "O" labels.

The following describes the deep learning models:

(a) Single Task learners (Baselines) BiLSTM-CRF consists of an embedding layer of 100 hidden units followed by a BiLSTM layer for the current utterance and similarly for coarse-POS tags, followed by a merge layer and dense layer and finally a CRF layer. The BERT-CRF architecture has a similar architecture to BiLSTM-CRF except it uses a BERT layer (corresponding to the pre-trained cased model) to output 768 dimensional contextual embeddings for the utterance input and an embedding layer and BiLSTM layer to process POS tag input. Both models are trained on the target DTR data.

(b) Sequential Transfer Task Learners (STL) The models are trained on the NER data first using a CRF layer with 23 output dimensions to build pre-trained models. Then, the CRF layer is replaced with a new untrained CRF layer with 3 dimensions output for fine tuning with the DTR data.

(c) Multi Task Learners (MTL) In both BiLSTM-CRF and BERT-CRF, the model architecture is altered to share weights from all the layers prior to the CRF layer between the NER and DTR tasks. The CRF layer cannot be shared due to difference in number of possible labels for the two tasks.

Results in table 2 show that transfer learning boosts the performance of the deep learning models. In particular, the multi-task learners (i.e., BiLSTM-CRF-MultiL and BERT-CRF-MultiL) statistically significantly \(^6\) \((p < 0.001)\) outperform the baselines (i.e., BiLSTM-CRF, BERT-CRF) by over 10%\(^6\)One-way Anova with post-hoc Tukey HSD.

\(^4\)https://sklearn-crfsuite.readthedocs.io/en/latest/
\(^5\)https://keras.io/
\(^6\)One-way Anova with post-hoc Tukey HSD.
Figure 2: The user (inside the circle) currently has visualization "08-3" on the screen and is asking to construct "future" visualization "09" (in dashed lines). Language understanding creates user action (1); then the dialogue manager takes dialogue history (2) and creates agent action (3); finally the state tracker updates dialogue history (4).

Table 2: Text ref. detection using transfer learning. CRF statistically significantly outperforms other models.

F1. This is consistent with the literature which indicates weight sharing allows increased sharing of knowledge between similar neural network architectures.

Table 2 also indicates CRF performs statistically significantly better than all other models. This suggests that auxiliary tasks in addition to NER may be necessary to further see improvement as well as adding features other than POS tags. This reaffirms our choice for the detection framework (i.e., CRF), which we use in the evaluation of the whole reference resolution pipeline in the following. Note that only detection can benefit from deep learning / transfer learning, since it can be set up as a classification problem.

5.2 Reference Resolution Pipeline

Detection. Table 3 shows how accurately our model detects the annotated labels for the reference resolution task; recall there are a total of 54 gesture and 80 text references cross setup and request, achieving an overall accuracy score of 52.2%. Note that the model performed worst on gesture references. One possible reason for this is that the heuristic rule for deciding whether a gesture is referential may need to be relaxed (we currently ignore any gesture that did not co-occur with a text reference). Another factor could be that our CRF tagger model for detecting text references may need further exploration potentially taking gesture features into account since they often co-occur.

Semantic Structure Construction. Overall, our model achieved an accuracy score of 66.2% for detecting slots as part of the new entity establishment process for visualization features. Further analysis
Table 5: Resolution accuracy for varying window sizes.

| Ref     | Setup Win. = | AR Win. = |
|---------|--------------|-----------|
|         | 0            | 1         | ∞         | 0        | 1         | ∞         |
| Gest.   | 0.0          | 93.0      | 100.0     | 0.0      | 68.4      | 100.0     |
| Text    | 0.0          | 85.3      | 85.3      | 0.0      | 74.4      | 68.3      |
| All     | 0.0          | 82.6      | 87.0      | 0.0      | 73.0      | 82.9      |

from Table 4 shows that in over half of all utterances (57.6%), all the slots were detected while in 85.3% of the utterances, at least 75% of them were successfully detected. We will discuss follow-up requests shortly.

**Resolution.** Accuracy on resolving text and gesture references for varying WINDOW sizes is shown in Table 5. Focusing first on unlimited window size (i.e., ∞ for all referent visualization candidates are eligible), we see 100% accuracy for gesture references for both setup and request as expected: ground truth gestures are used for input for the experiment. This also validates that our DM is correctly performing state tracking. Next, text references found in ARs are correctly resolved for over 68% while for setup it is 85%. Overall accuracy score for resolving references is 83.6%.

Turning now to other window sizes, an expected trend can be observed in Table 5: as one increases the number of eligible candidate referents for resolution, there is an overall increase in correctly resolved visualization references. In particular dialogue context boosts accuracy by approximately 10% for ARs and 4% for setup. However, text references struggle with increasing window size, suggesting our linear decay function may need further tuning to better model the user preference behavior. Further analysis actually shows similar behavior between the model and user: in over 75% of the time the most recent visualization is chosen by both, however for further away entries the linear decay function penalizes them too harshly leading to the model rarely choosing them.

**Under-specification.** Table 4 shows in over half the cases (51.2%), at least 75% of slots in follow up requests are detected by our model. Moreover Table 7 shows that the model achieves close to a 6% boost in accuracy, however the model struggles to identify slots beyond one request in follow up sequences of requests. Next, Table 6 shows model performance on plot type prediction. The model predicts between three kinds of plots including heat map, line chart, and bar graphs. Bar graphs achieved superior performance. Over half the visualizations (56%) shown to the user are bar graphs. Heat maps performed worst; it is not always obvious when to use heat maps. For instance, asking for crimes by neighborhood could be shown as a bar graph to quickly determine the safest and most dangerous neighborhoods whereas as a heat map the location of the neighborhoods is also shown.

### 6 Conclusions and Future Work

We have presented a reference resolution model for multi-modal visualization dialogue. In particular, the model resolves visualization references in the context of the current interaction, crucially tracking visualizations constantly being added and removed from the screen. Also the model is central to the creation of new visualizations: visualization features via entity introduction help the model know how to refer to a visualization later on.

We plan to address potential extensions in future work. First, the model assumes proximity to measure the word dependency relationship between a referring expression and nearby slots (e.g., "months of year" is in the same utterance as "this graph"). Incorporating additional linguistic information via the dependency parse tree can capture this relationship more reliably. Other worthwhile avenues to explore include ways to better model user behavior for referring to more distant visualizations and adapting our resolution algorithm beyond the cosine similarity measure to more sophisticated machine learning based approaches to take advantage of the rich visualization feature space in our case. Also, as part of our broader research objectives, we intend to conduct studies with real users interacting with our visualization system, by integrating our resolution pipeline with the first version of the assistant: there, we used an Android app that employs...
the Google Speech API to perform speech-to-text
on the click of a button and a gesture recognition
system that recognizes pointing gestures using a
Microsoft Kinect camera calibrated for our large
screen display.

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