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Event Prediction in Event-Centric Knowledge Graph Using BERT

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Objectives of this Challenge,

- Develop AI to support safety in the home in an aging society
- The task of this challenge is to collect information to understand the behavior in the home as a basis for the above purpose

Table of Contents

- This document outlines our approach and provides details of the results and other relevant information
- Table of Contents (Our Approach)
  - Structural Transformation of Knowledge Graphs
  - Prediction by applying a hole-filling problem with BERT for event-centered knowledge graphs
  - Summary and future tasks

Task we tackled

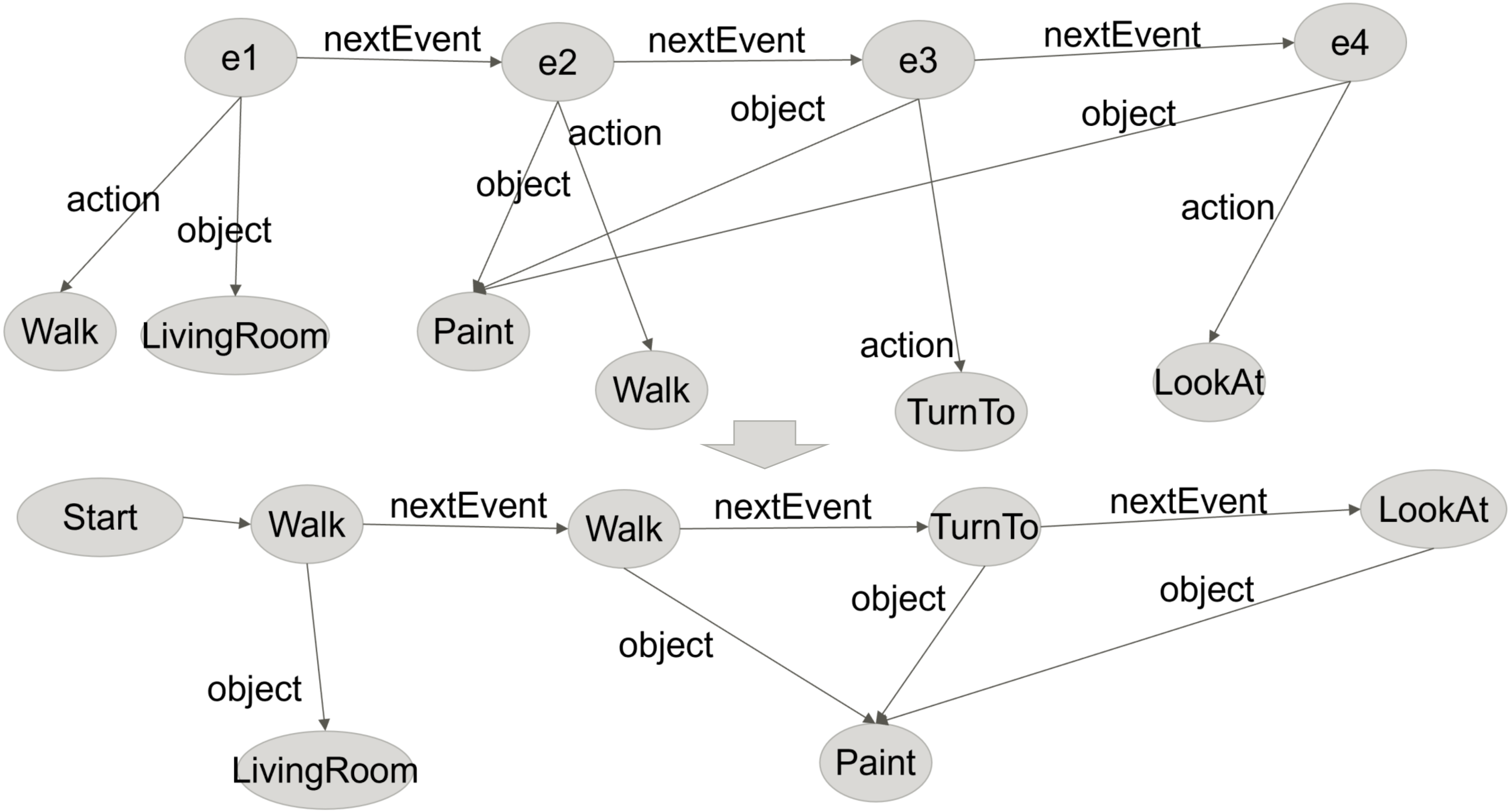
- Task 2:
  - Measure actions from an incomplete knowledge graph or scene graph
  - Answers Q1 to Q8 for each scenario provided.

  - Questions:
    - Q1: How many times did he enter each room?
    - Q2: How many times did he perform each action?
    - Q3: What action did he take after entering the kitchen?
    - Q4: What action did he take before entering the kitchen for the first time?
    - Q5: When, where, and what did he pick up(grab)?
    - Q6: What is he doing 10 seconds after the start?
    - Q7: Extract the relationship between objects at the initial state and after 10 seconds.
    - Q8: Extract changes in the state of objects from the initial state to 20 seconds later.

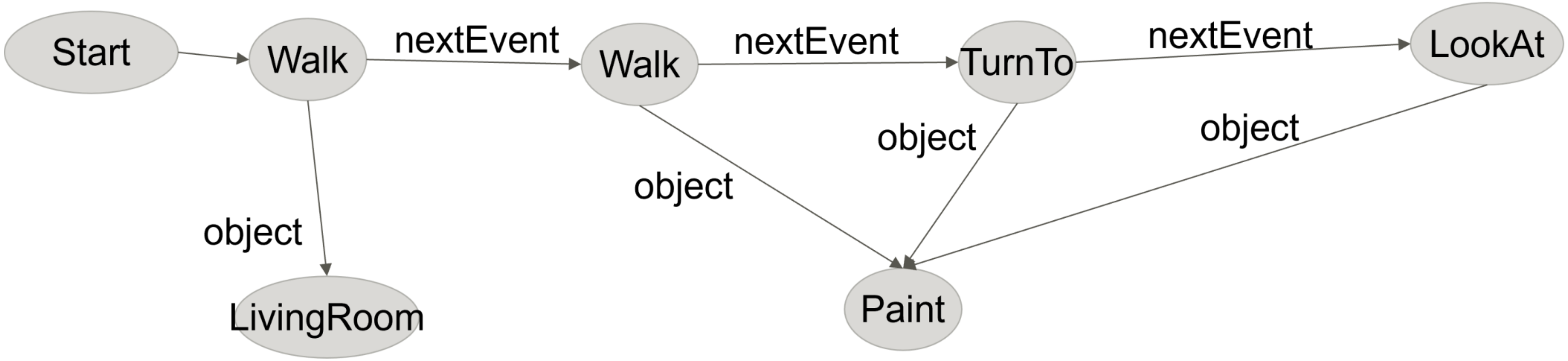
What we have done for the task

- Prediction of event-centered knowledge graphs by applying BERT to fill holes in the IKGRC knowledge graphs

Structural Transformation of Knowledge Graph



Prediction by applying a hole-filling problem



- Generating graph walks
  - Start→nextEvent→Walk
  - Walk→object→LivingRoom
  - Start→nextEvent→Walk→object→LivingRoom→nextEvent→Walk
  - Walk→object→Paint→nextEvent→TurnTo→object→Paint
  - TurnTo→object→Paint→nextEvent→LookAt

Learning graph walks with BERT

- Input
  - Walk→object→Paint→nextEvent→XXX→object→Paint
- Output
  - Walk→object→Paint→nextEvent→TurnTo→object→Paint

- BERT[2]:Bidirectional transformers proposed by Google

[2] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pretraining of deep bidirectional transformers for language understanding,”

Experiments

- Data
  - IKGRC Knowledge Graph (Version 3.0)
    ※ This version is older than the current version
    - Number of knowledge graph: 704
    - One knowledge graph of an activity has five events on average
    - One knowledge graph has 71,000 triples on average

- Experiment Data
  - Training Data
    - We picked 100 knowledge graphs at random from the 704 knowledge graphs
    - We removed the coordinate data of objects and text data
  - Test Data
    - We picked 20 knowledge graphs out of training data from the 704 knowledge graphs
    - We removed 20% of actions and objects from the knowledge graphs

Example of prediction

- Input
  - Walk→object→Paint→nextEvent→XXX→object→Paint
  - XXX→object→Paint→nextEvent→LookAt
  - Walk→nextEvent→XXX→object→Paint→nextEvent→LookAt
- Output
  - Walk→object→Paint→nextEvent→TurnTo→object→Paint
  - LookAt→object→Paint→nextEvent→LookAt
  - Walk→nextEvent→TurnTo→object→Paint→nextEvent→LookAt

  - 2 TurnTo and 1 LookAt→Prediction：TurnTo

Accuracy Comparison

model	HIT@1
BERT(Ours)	0.82
TransE	0.43
ComplEx	0.52
CBOW	0.48
Skip Gram	0.38

The scores of TransE and ComplEx are based on the manner of the link prediction from subject and predicate
The scores CBOW and Skip Graph are in the same manner as the proposed method in [3]

[3] J. Portisch, N. Heist, and H. Paulheim, “Knowledge graph embedding for data mining vs. knowledge graph e
- two sides of the same coin?”

Score: Task2

- This is not applicable.
- We have not applied our method to the current whole data.

Publicly accessible repository

- We don’t have a public repository for this experiment.

Discussion

- Our method performed better than traditional link prediction methods, even though we only applied it to a small number of graphs.
- The embedding vector contains information about the connection relationships of other nodes.
- When predicting using sequences, more information is used, which we believe contributes to the increase in accuracy.
- Converting to an action-centered graph seems to have a positive effect.
  - We cannot make a direct comparison due to different conditions

Summary

- We tackled Task 2 of this challenge

- Our approach is
  - Transforming the knowledge graph from event-centric to action-centric
  - Predicting by applying a hole-filling problem with BERT

- We have not had the score for the episodes for the current dataset