Entity Summarization with User Feedback

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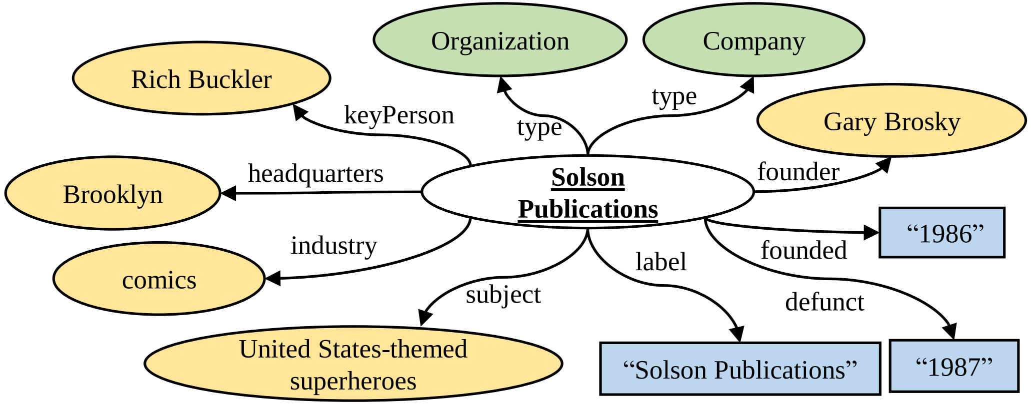
Entity Summarization

- RDF Dataset: T
  - triple $t \in T$: $\langle subj, pred, obj \rangle$
- Entity Description: Desc(e)
  - $Desc(e) = \{t \in T: subj(t)=e \text{ or } obj(t)=e\}$
  - $t \in Desc(e)$: $\langle e, prop, value \rangle$
- Entity Summarization: S(e, k)
  - $S \subseteq Desc(e)$, $|S| \leq k$



Entity Summarization Methods

- **Goal**
  - to satisfy users' information needs

- **Limitations**
  - have large diff from user-created (F1<0.6)

    => do not meet users' expectations
  - summaries are static

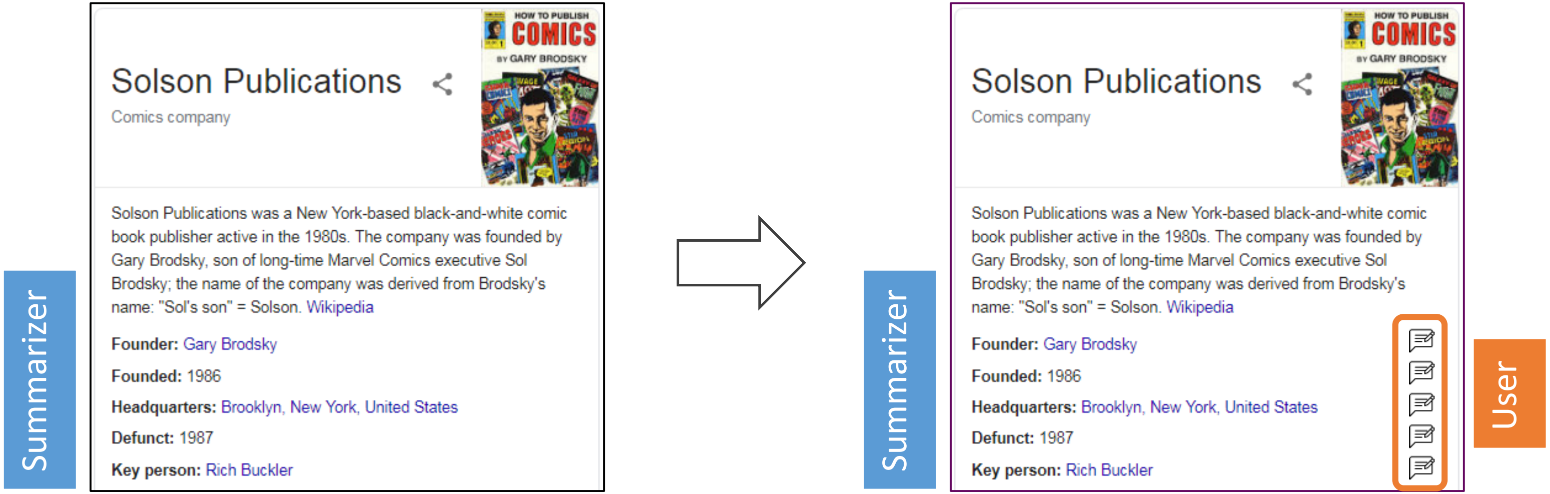
    => cannot adjust to users

F-measure of Entity Summarizers on ESBM Benchmark

	DBpedia		LinkedMDB	
	$k = 5$	$k = 10$	$k = 5$	$k = 10$
RELIN	0.242	0.455	0.203	0.258
DIVERSUM	0.249	0.507	0.207	0.358
FACES	0.270	0.428	0.169	0.263
FACES-E	0.280	0.488	0.313	0.393
CD	0.283	0.513	0.217	0.331
LinkSUM	0.287	0.486	0.140	0.279
ORACLE	0.595	0.713	0.619	0.678

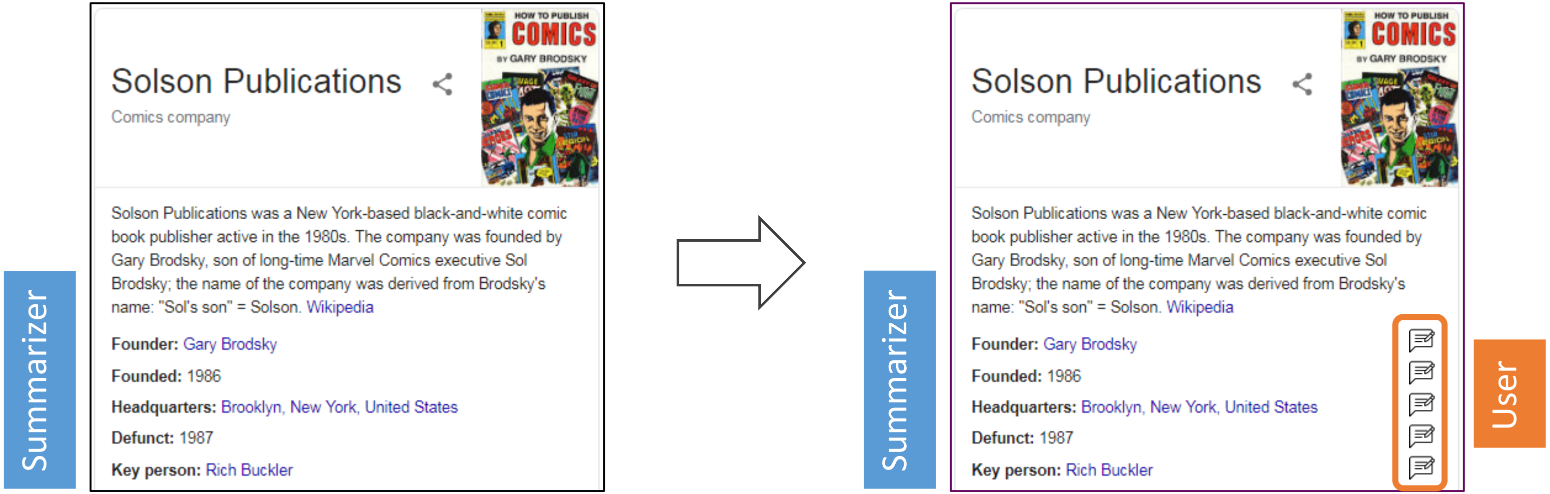
A lack of mechanisms for improving an entity summary when its quality could not satisfy users' information needs.

Adding User in the Loop



- Our proposal: cooperation between summarizer and user
  - involve users in the summarization process
  - ask users for feedback
  - utilize user's feedback when computing summaries

Adding User in the Loop



- Research Challenges

  [C1] Cooperative <u>process</u> of 2 agents

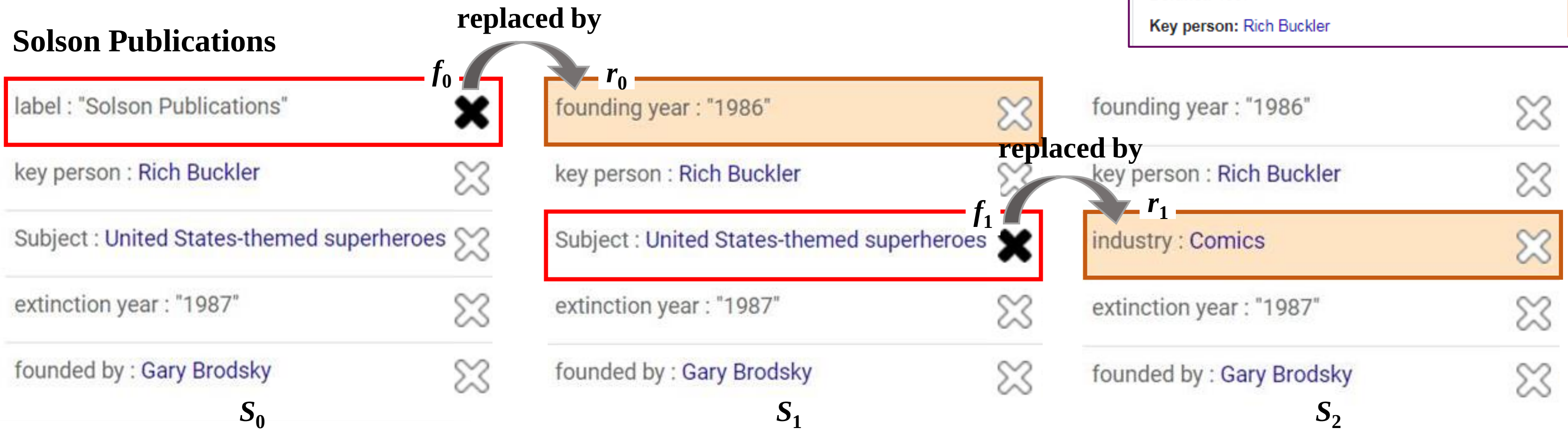
  – How to represent the process?

  [C2] Combining <u>results of actions</u> of 2 agents

  – How to represent interdependence between summary and feedback?

Cross-Replace Scenario

- Cooperation Process
  - Summarizer: presents (current) summary S_i
  - User: crosses off an irrelevant triple as negative feedback f_i
  - Summarizer: replaces it with a new triple r_i, presents an improved summary S_{i+1}
  - User: … (repeated)

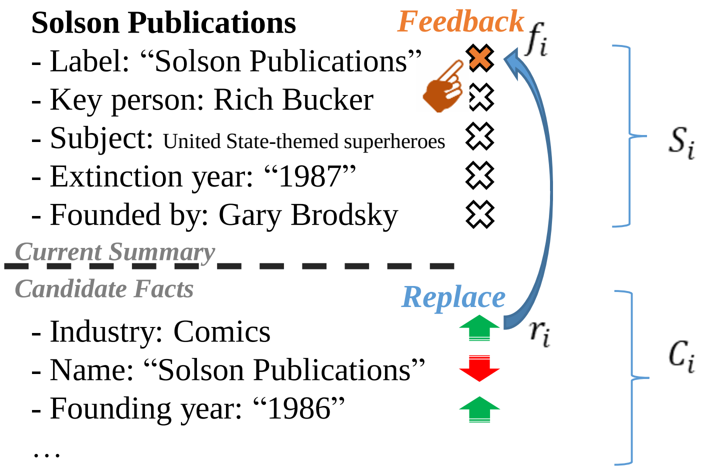


Our Approach: DRESSED

- [C1] Representation of the Cross-Replace Scenario
  - Markov Decision Process (MDP) based modeling
  - Summarizer = reinforcement learning agent

Setting:
- agent: summarizer
- environment: Desc(e), user

$$
\begin{aligned}
\text{state:} \quad & Z_i = \langle S_i, F_i, C_i, f_i \rangle \,, \\
\text{action:} \quad & A_i = r_i \,, \\
\text{policy:} \quad & \pi_{\boldsymbol{\theta}}(t|Z_i) = \frac{\exp(\mathtt{score}(t|Z_i, \boldsymbol{\theta}))}{\sum_{t' \in C_i} \exp(\mathtt{score}(t'|Z_i, \boldsymbol{\theta}))} \,, \\
\text{reward:} \quad & R_{i+1} = \rho(Z_i, A_i) = \frac{\mathtt{rel}(r_i)}{\log(i+2)} \,, \\
\text{transition:} \quad & Z_{i+1} = \tau(Z_i, A_i) = \langle S_{i+1}, F_{i+1}, C_{i+1}, f_{i+1} \rangle \,, \\
\text{initialization:} \quad & Z_0 = \langle S_0, \emptyset, (\mathtt{Desc}(e) \setminus S_0), f_0 \rangle \,.
\end{aligned}
$$



Our Approach: DRESSED

- [C2] Representation of Triple Interdependence
  - Policy Network
    - Encoding triples
    - Encoding sets of triples
    - Encoding triple interdependence and scoring candidates
    - Selecting replacement triple

$$\text{policy:} \quad \pi_{\boldsymbol{\theta}}(t|Z_i) = \frac{\exp(\texttt{score}(t|Z_i,\boldsymbol{\theta}))}{\sum_{t' \in C_i} \exp(\texttt{score}(t'|Z_i,\boldsymbol{\theta}))}$$

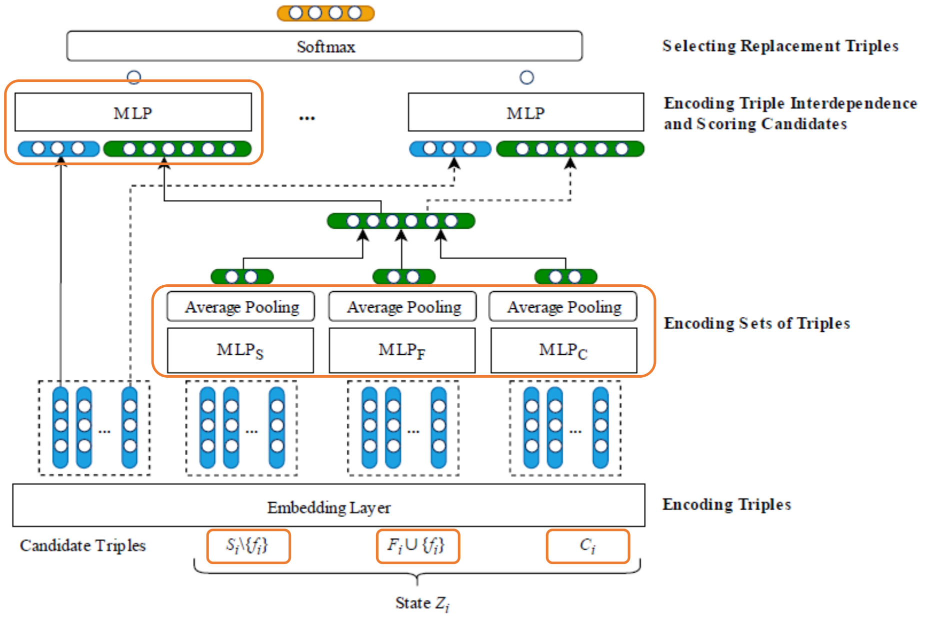


Fig. 2. Policy network.

Our Approach: DRESSED

- Policy Learning
  - Learning task: to find a policy that maximize the expected reward

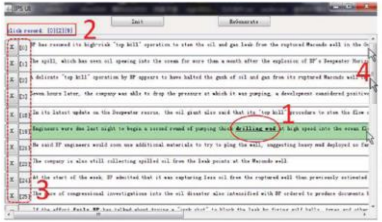
$$J(\boldsymbol{\theta}) = \mathbb{E}_{\xi\sim\pi_{\boldsymbol{\theta}}}[\sum_{i=1}^{I}\gamma^{i-1}R_i]\,,$$

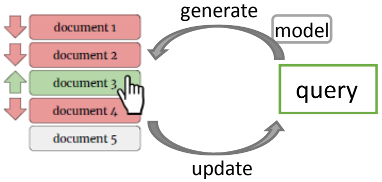
  - REINFORCE: a standard policy gradient method in reinforcement learning
    - to maximize the expected reward

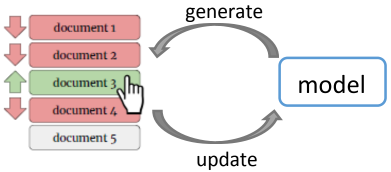
$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \gamma^i G_i \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(A_i|Z_i)\,, \quad \text{where } G_i = \sum_{j=i+1}^{I}\gamma^{j-i-1}R_j\,.$$

Baselines Adapted for Evaluation

- Entity Summarization
  (not utilize user feedback)
  - ***FACES-E***: rank triples and select top-k as summary
- Interactive Document Summarization
  (Re-compute doc summaries utilizing user feedback)
  - ***IPS***
    - positive feedback
- Interactive Document Retrieval
  (Re-rank retrieved documents based on user feedback)
  - ***NRF***
    - negative relevance feedback
    - query-based
  - ***PDGD*** -L, -N
    - positive feedback
    - SOTA online learning to rank
    - utilize user feedback for model selection
      (not as input of the model)







Experiment 1: User Study

- **Setting**
  - 24 participants
  - train: Entity Summarization Benchmark (ESBM)
  - test: re-sampled entities from DBpedia and LinkedMDB

Metrics:

- I = number of iterations
- Q_{rplc} = user rating of suggested replacements (1-5)
- Q_{stop} = user rating of the final summary after all iterations (1-5)

- **Results**
  - DRESSED: in general best-performing
  - with FACES-E and DRESSED
    - users stop quickly: I < 4
    - obtain reasonably good results: Q_stop > 4
    - replacement triples selected by DRESSED significantly better than the ones of FACES-E

	I	Q_{stop}	Q_{rplc}
FACES-E	$3.26_{\pm 2.83}$ – ▲ ○	$4.25_{\pm 0.85}$ – ▲ ○	$3.51_{\pm 1.05}$ – ▲ ▼
IPS	$4.18_{\pm 4.99}$ ▼ – ▼	$3.95_{\pm 1.05}$ ▼ – ▼	$3.09_{\pm 1.22}$ ▼ – ▼
DRESSED	$3.05_{\pm 2.70}$ ○ ▲ –	$4.25_{\pm 0.87}$ ○ ▲ –	$3.65_{\pm 1.04}$ ▲ ▲ –

Experiment 2: Offline Evaluation

- **Benchmarks**
  - ESBM (ESBM-D, ESBM-L), FED
- **Metrics**
  - **NDCF**: for summary sequence
    - Normalized Discounted Cumulative F1
  - **NDCG**: for replacement sequence
    - Normalized Discounted Cumulative Gain

- **Results**

  DRESSED outperforms
  - all baselines
  - on all datasets

  DRESSED significantly outperforms
  - in most cases

	ESBM-D		ESBM-L		FED	
	NDCF@I	NDCG@I	NDCF@I	NDCG@I	NDCF@I	NDCG@I
FACES-E	$.435_{\pm.022}$ –▲▲▼▼▼	$.620_{\pm.017}$ –▲▲▼▼▼	$.373_{\pm.028}$ –▲▲▼▼▼	$.585_{\pm.027}$ –▲▲▼▼▼	$.263_{\pm.067}$ –▲▲▼▼▼	$.573_{\pm.063}$ –▲▲▼▼▼
IPS	$.405_{\pm.026}$ ▼–○▼▼▼	$.553_{\pm.023}$ ▼–○▼▼▼	$.278_{\pm.030}$ ▼–▼▼▼▼	$.410_{\pm.042}$ ▼–▼▼▼▼	$.212_{\pm.027}$ ▼–○▼▼▼	$.497_{\pm.009}$ ▼–▼▼▼▼
NRF	$.407_{\pm.021}$ ▼○–▼▼▼	$.554_{\pm.016}$ ▼○–▼▼▼	$.325_{\pm.029}$ ▼▲–▼▼▼	$.503_{\pm.034}$ ▼▲–▼▼▼	$.218_{\pm.033}$ ▼○–▼▼▼	$.510_{\pm.019}$ ▼▲–▼▼▼
PDGD-L	$.445_{\pm.037}$ ▲▲▲–○▽	$.632_{\pm.029}$ ▲▲▲–○▼	$.446_{\pm.027}$ ▲▲▲–○▼	$.699_{\pm.030}$ ▲▲▲–○▼	$.300_{\pm.031}$ ▲▲▲–○▼	$.628_{\pm.025}$ ▲▲▲–○▼
PDGD-N	$.447_{\pm.037}$ ▲▲▲○–○	$.636_{\pm.030}$ ▲▲▲○–▽	$.446_{\pm.025}$ ▲▲▲○–▼	$.698_{\pm.034}$ ▲▲▲○–▼	$.303_{\pm.033}$ ▲▲▲○–▼	$.630_{\pm.030}$ ▲▲▲○–▼
DRESSED	$.455_{\pm.032}$ ▲▲▲△○–	$.645_{\pm.028}$ ▲▲▲▲△–	$.481_{\pm.030}$ ▲▲▲▲▲–	$.760_{\pm.029}$ ▲▲▲▲▲–	$.316_{\pm.038}$ ▲▲▲▲▲–	$.644_{\pm.042}$ ▲▲▲▲▲–

Experiment 2: Offline Evaluation

- Iterations
  - DRESSED is consistently above all the baselines
  - DRESSED better exploits early feedback to quickly improve computed summaries

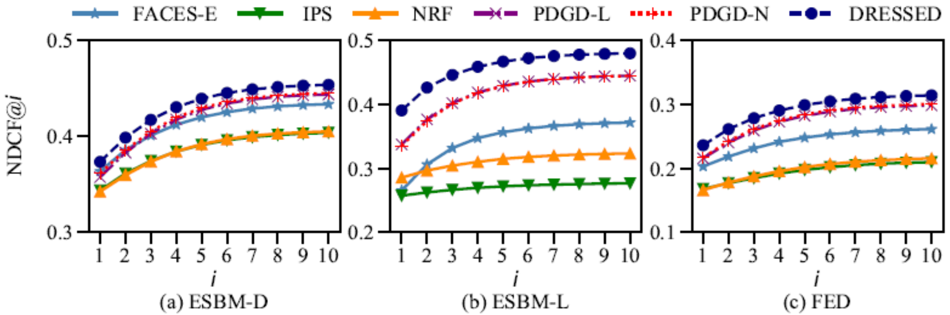


Fig. 3. Results of offline evaluation over varying numbers of iterations (NDCF@i).

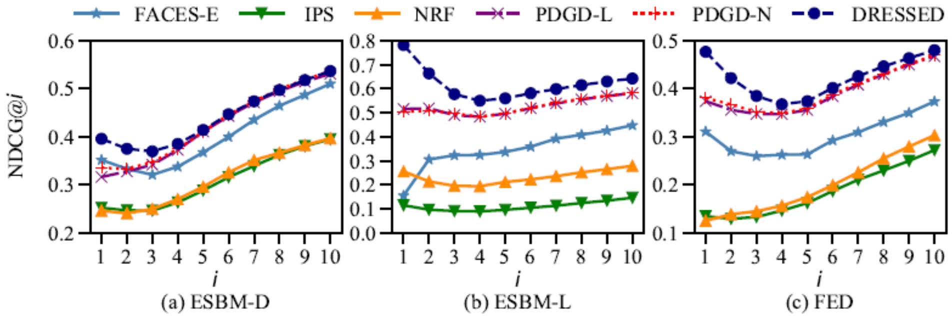


Fig. 4. Results of offline evaluation over varying numbers of iterations (NDCG@i).

Conclusion and Future Work

- Our Approach: DRESSED
  - showed better performance than baselines
  - has the potential to replace static entity cards

- Future Work
  - cross-replace scenario
    - can be extended to support other scenarios:
      - multi-feedback, without replacement, positive feedback
  - extend the scope of entity summary
    - deal with paths, more complex structures, RDF sentence

Take-home Message

- Contributions
  - The first research effort to improve entity summarization with user feedback.
  - A representation of entity summarization with iterative userfeedback.
    - cross-replace scenario, MDP
  - A representation of set of triples and their interdependence as a novel DNN.
    - DRESSED, solve by RL
  - The first empirical study of entity summarization with user feedback.
    - based on real users and simulated users

- DRESSED
  - **D**eep **R**einforced **E**ntity **S**ummarization with u**S**er f**E**edback
  - GitHub Repository: nju-websoft/DRESSED

Thank you !

Questions ?