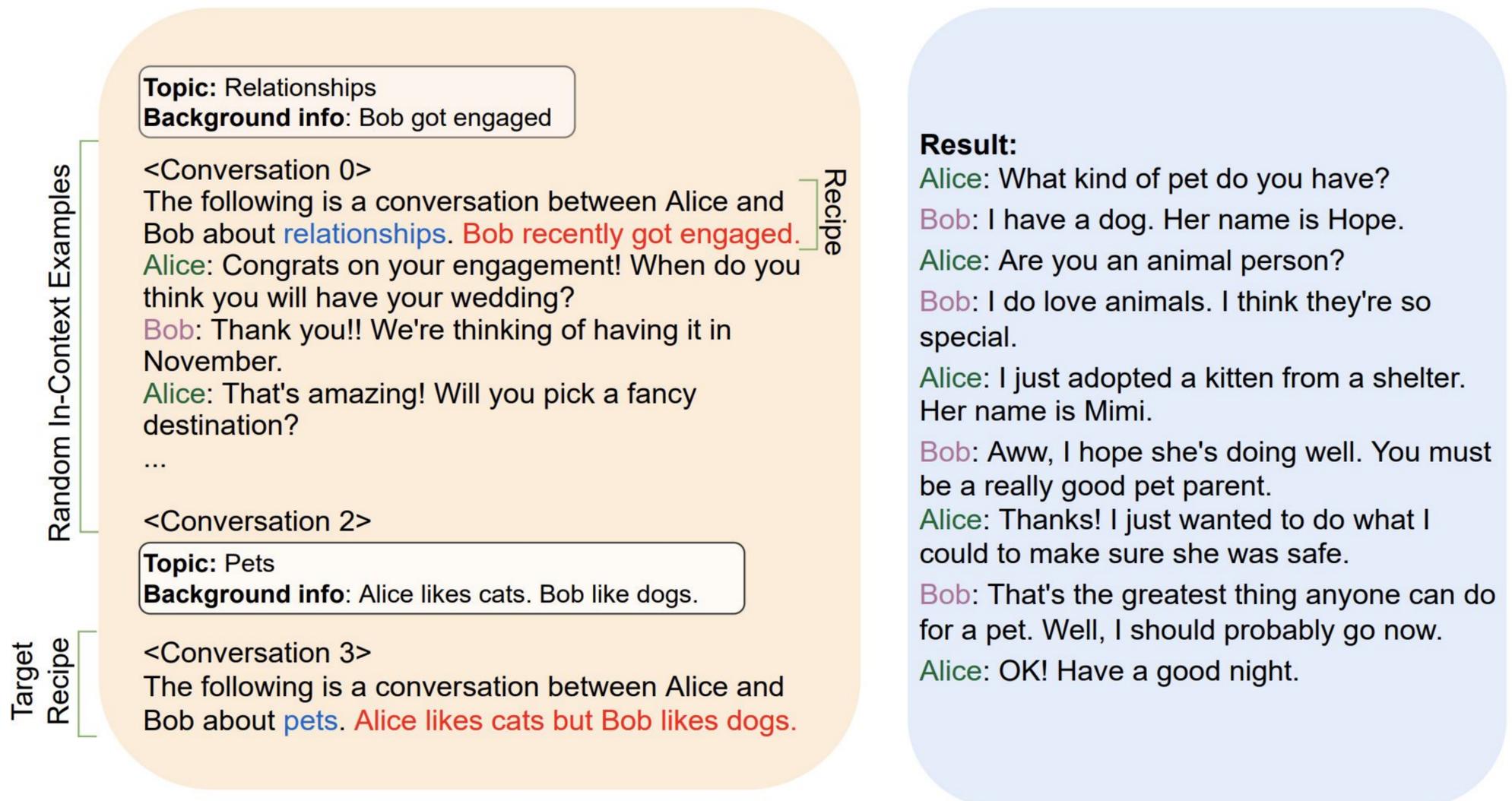


PLACES: Prompting Language Models for Social Conversation Synthesis

Maximillian Chen, Alexandros Papangelis, Chenyang Tao, Andy Rosenbaum, Seokhwan Kim, Yang Liu, Zhou Yu, Dilek Hakkani-Tur

Distilling Synthetic Conversations from Large Language Models



- **Have you ever struggled with finding the right dataset?** Maybe your dataset doesn't exist, your existing dataset is privacy-restricted, or you aren't happy with your data quality.
- **You can distill high-quality conversations by prompting large language models!** By providing expert-written in-context examples and conversation "recipes," one can generate humanlike synthetic conversations with high semantic control.

Synthetic Conversation Quality

Source	Interesting	Coherent	Natural	Consistent
<i>Human-Collected</i>				
DailyDialog	3.44	4.51	4.85	4.57
Topical Chat	4.55	4.39	4.92	4.87
<i>PLACES</i>				
GPT-J 6B	3.96*	4.49	4.86	4.36
GPT-NeoX 20B	3.81*	4.40	4.63	4.35
OPT 30B	4.13*	4.61 *†	4.82	4.63

- **Human evaluations** of synthetic conversations match or outperform human-annotated datasets

Dimension	DD-IC	TC-IC	HW-IC
Interesting	3.82	4.35	4.27*
Coherent	4.48	4.56	4.77 *+
Natural	4.54	4.69	4.69 *
Consistent	4.76	4.87	4.86*
On-Topic	0.91	0.88	0.96 *+

- **In-context example selection matters:** expert-written examples (HW-IC) outperform crowdsourced conversation examples

Generalizing to Multiparty Conversations

Dimension	MPC	MELD	PLACES
Interesting	2.48	3.52	4.14 *
Coherent	2.40	3.68	4.65 *
Natural	2.69	3.69	4.47 *
Consistent	2.96	3.83	4.65 *
Comprehensible	2.48	3.83	4.80 *
Balanced Engagement	3.45	4.00	4.89 *

- **PLACES** generalizes to the multiparty conversation case, outperforming both MELD (*Friends* transcripts) and MPC (online chats)

Paper



Code

