A Hybrid Retrieval-Generation Neural Conversation Model

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Direction

1. **Abstract & Introduction**
2. **Related work**
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5. **Conclusions and Future work**

1. Abstract & Introduction

- 현재 인공지능 개인 맞춤 시스템이 많은 인기를 얻고 있다
  - Amazon Alexa, Apple Siri, Microsoft Cortana
- 최근에 이런 챗봇 모델은 수작업을 줄이기 위해서 End to End Conversation 모델을 제시하고 있고 아래 대표적인 2개의 모델이 있다
- 1) Retrieval based, 2) Generation based 로 나누어 질 수 있음

1. Abstract & Introduction

- 1) Retrieval based
  - 1)질문이 들어오면 가장 유사한 답변을 Response Repository에서 찾은 다음 2)가장 유사한 질문을 re-rank하고 neural ranking모델이 최적의 답을 찾는다
  - 장점:
    - 사람의 답변에 유사한 답을 하며 Response에 대한 Controllable과 Explainable하다
    - Retrieval based 는 Response repository에 해당 질문과 가장 유사한 답변을 하기 때문에 다양한 주제에 대해서 Fluent 와 Informative 한 response를 함
  - 단점:
    - Response repository의 사이즈의 한계
    - Long tail context에 대해서 답변하기 어려움
    - Flexibility가 떨어짐 왜냐면 Response repository가 이미 Constructed 되어 있기 때문에

1. Abstract & Introduction

- 2) Generation based
  - Seq2seq모델을 바탕으로 Encoder 에서 conversation context의 representation을 학습하고, Decoder에서 response sequence를 생성한다
  - 장점:
    - 어떤 Topic에도 High Coherent new Response함
  - 단점:
    - Grounding Knowledge 부족으로 인한 Generic(일반적이고) Not Informative함
      - Ex)
        - “I Have no Idea”
    - Grammar Error 존재

1. Abstract & Introduction

- 두 메소드 차이 정리

Table 1: A comparison of retrieval-based methods and generation-based methods for data driven conversation models.

Item	Retrieval-based methods	Generation-based methods
Main techniques	Retrieval models; Neural ranking models	Seq2Seq models
Diversity	Usually good if similar contexts have diverse responses in the repository	Easy to generate bland or universal responses
Response length	Can be very long	Usually short
Context property	Easy for similar context in the repository; Hard for unseen context	Easy to generalize to unseen context
Efficiency	Building index takes long time; Retrieval is fast	Training takes long time; Decoding is fast
Flexibility	Fixed response set once the repository is constructed	Can generate new responses not covered in history
Fluency	Natural human utterances	Sometimes bad or contain grammar errors
Bottleneck	Size and coverage of the repository	Specific responses; Long text; Sparse data
Informativeness	Easy to retrieve informative content	Hard to integrate external factual knowledge
Controllability	Easy to control and explain	Difficult to control the actual generated content

1. Abstract & Introduction

- 이 논문에서는 두가지 기술의 Merits를 결합한 Hybrid neural conversation model을 제시
  - 1) Generation model에서 Response를 생성하고(Seq2seq모델),
  - 2) Retrieval Model 에서 Response candidates의 set을 Recall하고,
  - 3) neural ranking model이 1)과 2)으로부터best response candidate를 select한다(neural ranking model은 conversation pair의 representation과 matching feature를 학습)
    - 이를 학습하기 위해서 distante supervision을 제안하는데, retrieval 모델/generation모델에서 생성한 Response Candidates의 (Positive, Negative)label을 자동으로 추론 해서 Neural Ranking Model의 학습데이터를 제공

1. Abstract & Introduction

- 실험 결과는 Twitter와 Foursquare data에서 다른 2가지 모델보다 Outperform 하는 것을 보여줌
- Contribution
  - Retrieval-based model과 Generation-based model을 비교한 것
  - Hybrid neural conversational 모델을 제안한 것
  - Distant Supervision approach 제시
  - 자동 평가와 사람 평가에서 좋은 결과를 가져옴

2. Related work

- Neural Ranking Models
  - 3 Category
    - 1. Representation-focused models
      - Queries와 Documents의 Representation를 학습하고 이 둘의 유사도를 계산
    - 2. Interaction-focused model
      - Query-document의 쌍의 interaction matrix 계산해서 매칭
    - 3. 1, 2번 neural ranking모델을 혼합해서 사용 Lexical 과 semantic matching을 사용
  - 이 Approach에 사용한 모델은 Interaction-focused 모델에 속함

3. Our Approach

- 3.1 Problem Formulation
  - Conversation Context에서 u_i is the i-th context sequence
  - F factual snippets of text $F_i = \{f_{i1}, f_{i2}, \ldots, f_{iF}\}$

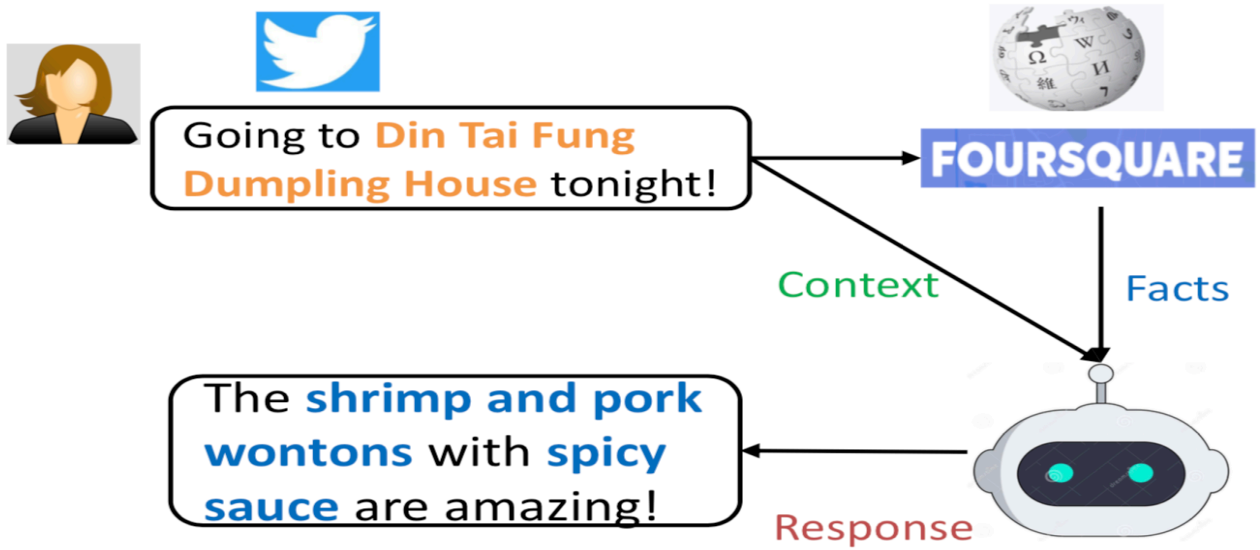

Figure 1: An example of the conversational response generation task. The factual information from external knowledge is denoted in blue color.

3. Our Approach

- 3.2 Method Overview
  - Hybrid Neural Conversation Model(HybridNCM)
    - 1)Generation module
      - Conversation Context ui 와 Fi (Fact)를 Seq2seq 모델에서 Response Candidate Gi Set을 생성
      - Context Encoder
        - Seq2seq model + attention mechanism
        - $h_t = RNN(u_t, h_{t-1})$,
        - 2 LSTM Layer
      - Fact Encoder
        - Context Encoder와 같은 Layer
      - Response Decoder
        - Next Word G_t를 생성, 2 LSTM Layer + attention

3. Our Approach

- 4) -> 이전 Decoder hidden state St-1 의 Attention at
- 8) Encoder의 Last output 을 가지고 Decoder 초기화

$$p(g|u_i, \mathcal{F}) = \prod_{t=1}^{L_g} p(g_t|g_{1:t-1}, u_i, \mathcal{F}) \tag{2}$$

$$\mathbf{E} = [\mathbf{h}_1, \cdots, \mathbf{h}_{L_u}, \bar{\mathbf{f}}^1, \cdots, \bar{\mathbf{f}}^F] \in \mathbb{R}^{H \times (L_u + F)} \tag{3}$$

$$\mathbf{a}_t = \text{softmax}\left(\mathbf{E}^T \mathbf{s}_{t-1}\right) \tag{4}$$

$$\mathbf{c}_t = \mathbf{E}\mathbf{a}_t \tag{5}$$

$$\mathbf{v}_t = \tanh\left([\mathbf{s}_{t-1}, \mathbf{c}_t]\right) \tag{6}$$

$$\mathbf{s}_t = \text{RNN}(\mathbf{v}_t, \mathbf{s}_{t-1}) \tag{7}$$

$$\mathbf{s}_0 = \varphi\left(\tanh\left(\mathbf{h}_{L_u} + \frac{1}{F}\sum_{j=1}^{F} \bar{\mathbf{f}}^j\right)\right) \tag{8}$$

- 이전 단어 다음에 나올 단어 예측 $p(g_t|g_{1:t-1}, u_i, \mathcal{F}) = \text{softmax}(\phi([\mathbf{s}_{t-1}, \mathbf{c}_t]))$

3. Our Approach

- Train and Decode

$$\mathcal{L}_g = -\frac{1}{|\mathcal{U}|} \sum_{y^*, u_i, \mathcal{F}} \log p(y^* | u_i, \mathcal{F}) \qquad (10)$$

  - Negative log-likelihood 를 모든 트레이닝 데이터에 대해서 훈련
  - Response를 생성하기 위해서 Beam search를 이용
  - 짧은 답변을 생성한 경우에 Penalty를 주기위해 log-likelihood 점수를 생성된 단어를 length로 나누어 준다

3. Our Approach

- Hybrid Neural Conversation Model(HybridNCM)
  - 2) Retrieval Module
    - “Context-Context Match” Approach
    - 모든 historical conversation context에서 현재 conversation context u_i를 매칭하여 Response candidate R_i를 생성

3. Our Approach

- Hybrid Neural Conversation Model(HybridNCM)
  - 3) Hybrid Ranking Module
    - Interaction Matching Matrix
      - $Y_i = G_i \cup R_i$
      - Generated Response G_i Set
      - Response Candidate R_i Set
      - Hybrid Ranking Candidate Re-Rank all candidate Y_i
      - Conversation Context u_i
    - Distant Supervision으로부터 라벨로 학습된 Hybrid Neural Ranker 를 통해서 all candidate Y_i Best response를 출력함
    - Fact는 사용하지 않고
    - Conversation Context u_i all candidate Y_i 의 Interaction Matching MatrixCNN과 MLP로 계산

3. Our Approach

- Hybrid Neural Conversation Model(HybridNCM)
  - Ranking을 매기 위한 데이터 구성
    - triples(u_i,y_{k+},y_{k-}), where y_{k+} and y_{k-} denote the positive and the negative response candidate 를 학습 데이터로 사용
  - 입력 Context와 적절한 Response를 평가하는 것이 쉽지 않고, 또 비용이 많이 들어가므로 입력된 Context에 대한 적절한 응답을 계산하는 것이 필요
  - 따라서 효과적으로 트레이닝 하기 위해서 Ranking module을 학습하기 위한 Training data를 생성할 필요가 있음
  - Hybrid ranking model에서 생성한 Repsonse Candidate Y_i 와 BLEU/ROUGE-L 과 값은 기법으로 Ground Truth를 비교한다. 이 비교를 통해서 Positive Candidate response와 정답과 다른 Negative candidate를 구별하고 Training data의 라벨로 만듬
  - Hybrid Ranking model의 Hinge Loss

$$\mathcal{L}_h = \sum_{i=1}^{I} \max(0, \epsilon - f(u_i, y_i^{k+}) + f(u_i, y_i^{k-})) + \lambda ||\Theta||_2^2 \qquad (13)$$

  - Relation Extraction기법에 영감을 받음
  - Negative 개념이 들어가는건 더 좋은 Response를 구별하기 위해서

3. Our Approach

- Total Architecture

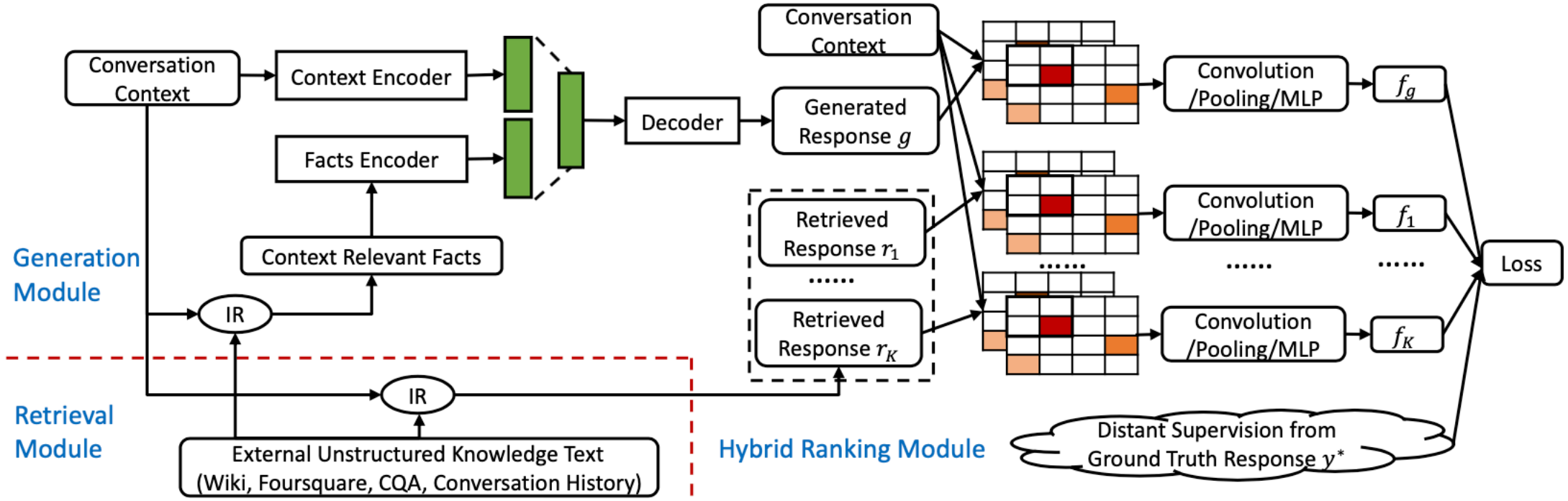

Figure 2: The architecture of the Hybrid Neural Conversation Model (HybridNCM).

4. Experiments

- 4.1 Data Set Description
  - Twitter, Foursquare Dataset

Table 3: Statistics of experimental data used in this paper.

Items	Train	Valid	Test
# Context-response pairs	1,059,370	2,067	2,066
# Facts	43,111,643	79,950	79,915
Avg # facts per context	40.70	38.68	38.68
Avg # words per facts	17.58	17.42	17.47
Avg # words per context	16.66	17.85	17.66
Avg # words per response	11.65	15.58	15.89

4. Experiments

- 4.2 Experimental Setup
  - 3가지 모델을 비교
    - Retrieval-based
    - Generation-based
    - Hybrid retrieval-generation method
      - 1) HybridNCM-RS
      - 2) HybridNCM-RSF(Fact Encoder 추가)
  - Seq2seq
  - Seq2seq-Fact(fact encoder 추가),
  - KNCM-MTask-R(Knowledge-grounded neural conversation model, 23 million general Twitter conversation, 1 million fact data) 최근 가장 좋은 모델
  - Evaluation
    - 생성된 response에 대한 BLEU와 ROUGE-L기법을 사용
    - Corpus Level에서 BLEU평가가 Sentence Level평가보다 더 사람의 평가에 상관성이 있다.
    - Lexical 에 diversity(Distinct-1과 Distinct-2 사용) 와 informativeness 를 평가
    - 사람의 평가도 들어감

4. Experiments

- 4.2 Experimental Setup
  - Parameter Settings

Models	Seq2Seq	Seq2Seq-Facts
Embedding size	512	256
# LSTM layers in encoder/decoder	2	2
LSTM hidden state size	512	256
Learning rate	0.0001	0.001
Learning rate decay	0.5	0.5
# Steps between validation	10000	5000
Patience of early stopping	10	10
Dropout	0.3	0.3

4. Experiments

- 4.3 Evaluation Results

Method	BLEU	ROUGE-L	Distinct-1	Distinct-2
Seq2Seq	0.5032	8.4432	2.36%	11.18%
Seq2Seq-Facts	0.5904	8.8291	1.91%	7.85%
KNCM-MTask-R	1.0800	\	7.08%	21.90%
Retrieval	1.2491	8.6302	**14.68%**	**58.71%**
HybridNCM-RS	1.3450	**10.4078**‡	11.30%	47.35%
HybridNCM-RSF	**1.3695**	10.3445‡	11.10%	46.01%

4. Experiments

- 4.3 Evaluation Results
  - 사람 평가
    - Appropriateness
    - Informativeness
    - 0(bad), +1(neutral, +2(good)

Comparision	Appropriateness					Informativeness				
Method	Mean	Bad(0)	Neutral(+1)	Good(+2)	Agreement	Mean	Bad(0)	Neutral(+1)	Good(+2)	Agreement
Seq2Seq	0.4733	61.67%	29.33%	9.00%	0.2852	0.2417	77.58%	20.67%	1.75%	0.4731
Seq2Seq-Facts	0.4758	62.50%	27.42%	10.08%	0.3057	0.3142	70.75%	27.08%	2.17%	0.4946
Retrieval	0.9425	34.42%	36.92%	28.67%	0.2664	0.8008	35.50%	48.92%	15.58%	0.3196
HybridNCM-RS	**1.1175**‡	27.83%	32.58%	39.58%	0.3010	**1.0650**‡	18.42%	56.67%	24.92%	0.1911
HybridNCM-RSF	1.0358‡	31.67%	33.08%	35.25%	0.2909	1.0292‡	20.42%	56.25%	23.33%	0.2248

4. Experiments

- 4.3 Evaluation Results
  - 사람 평가

Type	Appropriateness	Informativeness
Comparision	Win/Tie/Loss	Win/Tie/Loss
HNCM-RS v.s. Seq2Seq	0.71/0.15/0.14	0.84/0.10/0.06
HNCM-RSF v.s. Seq2Seq	0.68/0.16/0.16	0.82/0.11/0.07
HNCM-RS v.s. Seq2Seq-F	0.70/0.15/0.15	0.80/0.12/0.08
HNCM-RSF v.s. Seq2Seq-F	0.65/0.19/0.17	0.77/0.15/0.09
HNCM-RS v.s. Retrieval	0.43/0.31/0.26	0.50/0.31/0.18
HNCM-RSF v.s. Retrieval	0.41/0.30/0.29	0.50/0.28/0.22

4. Experiments

- 4.4 Analysis of Top Responses Selected By Re-Ranker

Item	HybridNCM-RS		HybridNCM-RSF	
#TestQNum	2066	100.00%	2066	100.00%
#PickedGenRes	179	8.66%	275	13.31%
#PickedRetRes	1887	91.34%	1791	86.69%
#PickedTop1BM25	279	13.50%	253	12.25%

4. Experiments

- 4.5 Impact of Distant Supervision Signals

Model	HybridNCM-RS		HybridNCM-RSF	
Supervision	BLEU	ROUGE-L	BLEU	ROUGE-L
BLEU-1	**1.3450**	**10.4078**	**1.3695**	**10.3445**
BLEU-2	1.1165	10.1584	0.8239	9.8575
ROUGE-L	1.1435	10.0928	0.9838	9.7961
SentBLEU	0.8326	9.2887	1.0631	9.6338

4. Experiments

- 4.6 Impact of Ratio of Positive Samples

	Supervision	BLEU-1		BLEU-2		ROUGE-L	
Model	# Positive	BLEU	ROUGE-L	BLEU	ROUGE-L	BLEU	ROUGE-L
HybridNCM-RS	k'=1	0.9022	8.9596	0.7547	8.8351	1.0964	8.9234
	k'=2	1.0649	9.7241	1.1099	9.9168	1.1019	9.6216
	k'=3	**1.3450**	**10.4078**	**1.1165**	**10.1584**	**1.1435**	**10.0928**
HybridNCM-RSF	k'=1	1.0223	9.2996	**1.1027**	9.2453	1.0035	9.2812
	k'=2	1.3284	9.8637	1.0175	9.8562	**1.0999**	**9.8061**
	k'=3	**1.3695**	**10.3445**	0.8239	**9.8575**	0.9838	9.7961

4. Experiments

- 4.7 Example and Case Study

Context	Donated to the [ENTITY] last night and now I have to listen to automated phone calls. It's enough to make me want to cancel.	
Method	r/g	System Output Response
Ground Truth	-	Ask them to put you on their internal dnc list. They will likely respect this, because future calls can get them charged.
Seq2Seq	g	I didn't get it. I didn't.
Seq2Seq-Facts	g	I'm sorry to hear that. Please dm us your email address so we can look into this. Thanks!
Retrieval	r	It's a known issue in LA county. I just got an email from my dm and tech and it should be good in 30 minutes or so.
HNCM-RS	r	We're listening and would like to know more and help with your experience. Please follow us so i can dm you our contact info. [ENTITY]
HNCM-RSF	g	We're sorry to hear this. Please dm us if you need assistance. Please dm us your contact info so we can look into this.

5. Conclusions and Future work

- Retrieval 과 Generation을 혼합하여 사용하고, 학습을 할때 Distant Supervision Approach를 이용해서 학습데이터를 자동으로 label화를 시킨다.
- 이를 통해서 실험에서 위와 같은 Approach가 효과가 있다고 증명하고 있다

Q&A

Thank you