

A REINFORCEMENT LEARNING-DRIVEN TRANSLATION MODEL FOR SEARCH-ORIENTED CONVERSATIONAL SYSTEMS

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MOTIVATION, BACKGROUND AND RESEARCH QUESTIONS

From conversational systems...

- ▶ Chit-chat conversational systems: simple conversations [1]
- ▶ Task-oriented conversational systems: closed world (slot-filling patterns, KB extractions, ...) [2,3]
- ▶ Users interact in natural language

CHALLENGE

Understand users' information needs expressed in natural language to identify relevant documents

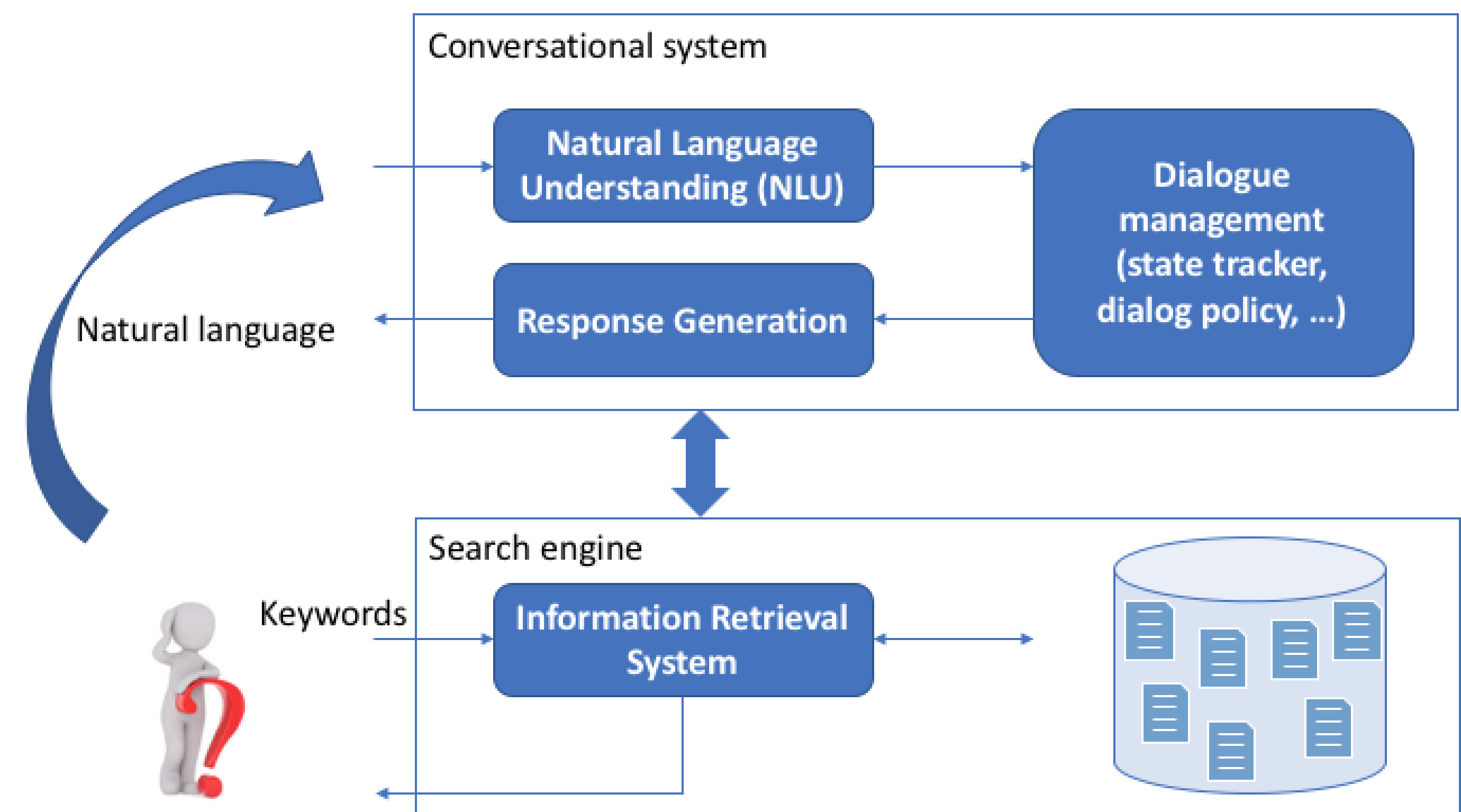
- ▶ Build keyword-based queries from natural language expressions
- ▶ "End-to-end" approach directly dealing with the NL expression

Related work

- ▶ Neural Machine translation models
 - ▶ Principle: Encoding the input in a latent representation space and decoding its latent representation in the target language
 - ▶ In our context: [4,5]
- ▶ Reinforcement learning approaches
 - ▶ Principle: Driving the approach by the task
 - ▶ In our context: [6]

... to search-oriented conversational systems

- ▶ "Open world"
 - ▶ Information needs are often ambiguous, vague, exploratory
 - ▶ Large document datasets, structured and unstructured information sources
- ▶ Information needs expressed through keywords



REINFORCEMENT LEARNING-DRIVEN TRANSLATION MODEL

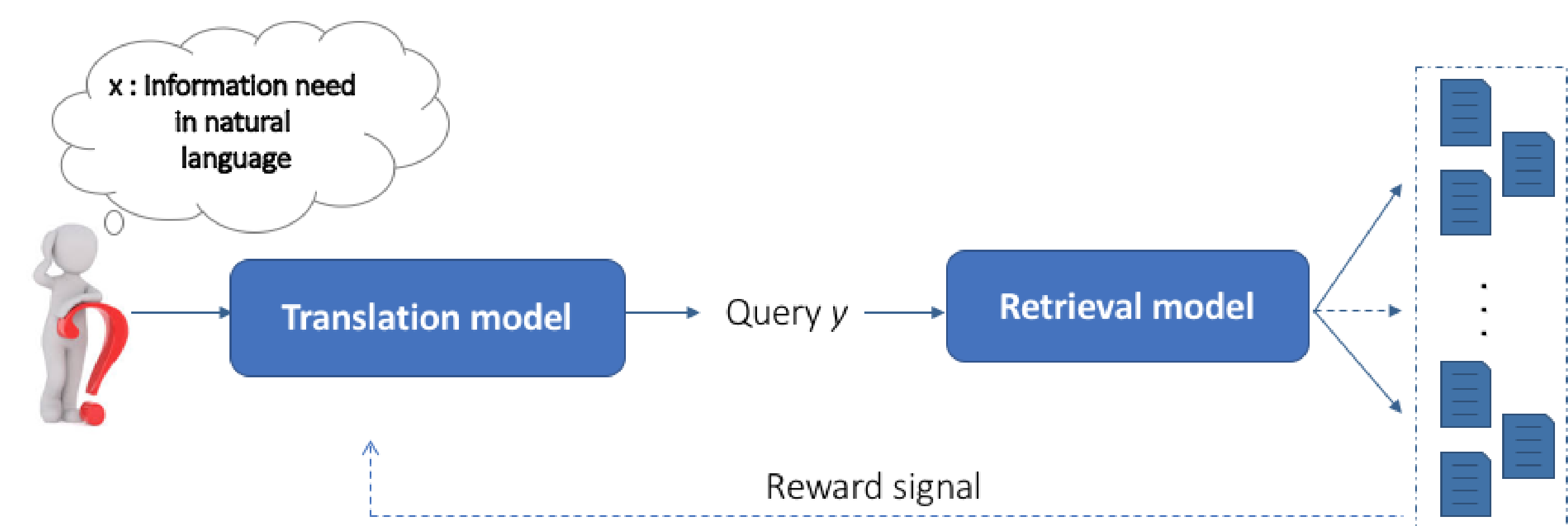
Notations

- ▶ $x = x_1, \dots, x_i, \dots, x_n$: NL user's information need.
- ▶ $y \in \{0, 1\}^n$: Key-word query.
- ▶ $y_i = 1$ if x_i exists in query y and 0 otherwise.

Problem formulation

f_θ : estimate the probability $p(y|x)$ of generating the keywords y given its natural language expression x , conditioned by $y_{<i}$.

$$p(y|x) = \prod_{y_i \in y} p(y_i | y_{<i}, x)$$



PRE-TRAINING WITH SUPERVISED MACHINE TRANSLATION

- ▶ NL-query pairs $D = \{(x^1, y^1), \dots, (x^k, y^k), \dots, (x^N, y^N)\}$
- ▶ Likelihood:

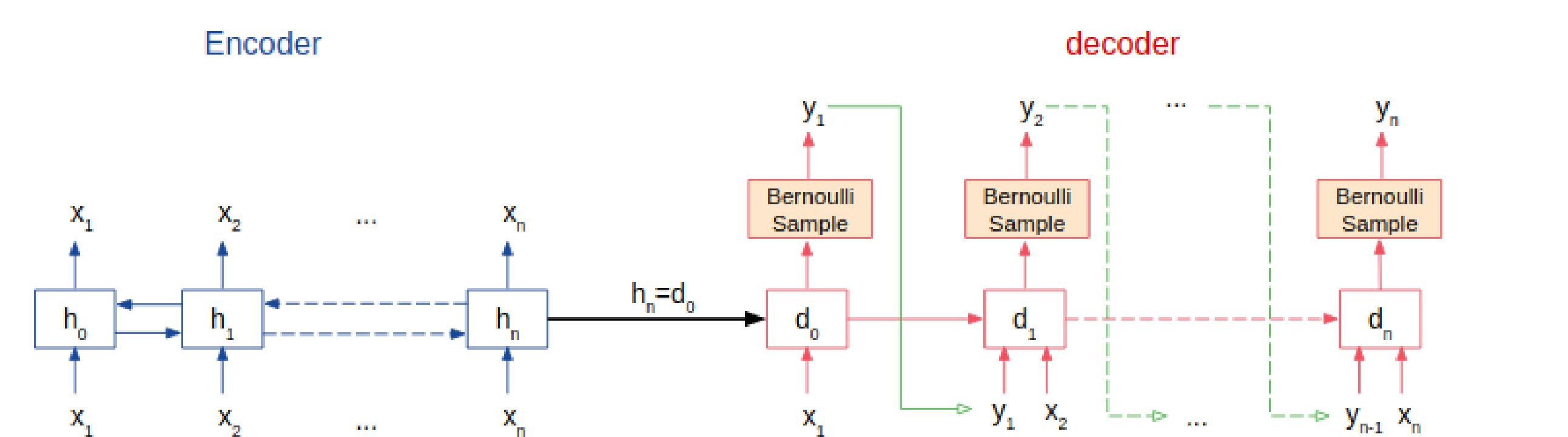
$$L_{SMT} = \sum_{(x^k, y^k) \in D} \log(f_\theta(x^k)) \text{ with } f_\theta(x^k) = \sum_{y_i^k \in y^k} \log(p(\hat{y}_i^k = y_i^k | \hat{y}_{<i}^k, x^k))$$

REFINING WITH REINFORCEMENT LEARNING

- ▶ Reward: $R(\hat{y}) = MAP(\hat{y}, \mathcal{D}_x)$ based on documents ranking using y .
- ▶ Actions: $\{0, 1\}$ or $\{\text{select}, \text{discard}\}$
- ▶ Likelihood:

$$L_{RL}(\theta) = \arg \max_{\theta} E_{(x; \mathcal{D}_x) \in GT} [R(\hat{y}) - \bar{R}]$$

NEURAL ARCHITECTURE



- ▶ Each element x_i of x is modeled through word embeddings w_{x_i}
- ▶ Bi-directional LSTM encoder (hidden state h_n)
- ▶ LSTM decoder (input: hidden vector h_n , the current word x_i , and a binary indicator y_{i-1} expressing whether previous word x_{i-1} has been selected or not)

EVALUATION

Datasets

- ▶ TREC Robust 2004: 250 NL-query pairs, 15.333 documents
- ▶ TREC Web 2000, 2001: 100 NL-query pairs, 11.47 documents

Baselines

- ▶ NL: the NL information need, TREC descriptions
- ▶ Q: original TREC titles
- ▶ Qbin: the binary formulated queries
- ▶ Random: randomly select 3 words from NL
- ▶ SMT: supervised machine translation
- ▶ RL: standalone reinforcement learning

Retrieval effectiveness

Baseline	TREC Robust(2004)		TREC Web (2000-2001)	
	MAP	%Chg	MAP	%Chg
NL	0.08925	+15.25% ***	0.15913	+12.88% *
Q	0.09804	+4.92%	0.16543	+8.58%
Q bin	0.08847	+16.26% *	0.17402	+3.22%
Random	0.01808	+468.91% ***	0.04060	+342.44% ***
SMT	0.06845	+50.27% ***	0.08891	+102.04% ***
RL	0.08983	+14.51% ***	0.16474	+9.04%
SMT+RL	0.10286		0.17963	

- ▶ Low results for **NL**: benefit of using keywords.
- ▶ **SMT+RL** overpasses **SMT**: benefit of reinforcement learning.
- ▶ **RL** baseline achieves relatively good retrieval performances.
- ▶ Reinforcement learning techniques are more effective with pre-training.

Examples of queries

- ▶ what are new methods of producing steel?
 - ▶ Original query (Q): steel producing
 - ▶ Binary query (Qbin): producing steel
 - ▶ Our model (SMT+RL): new methods of producing steel
- ▶ what are the advantages and or disadvantages of tooth implant?
 - ▶ Original query (Q): implant dentistry
 - ▶ Binary query (Qbin): implant
 - ▶ Our model (SMT+RL): advantages disadvantages tooth implant

CONCLUSION

- ▶ A selection model translating users' information need in NL into keyword queries
- ▶ Based on supervised machine translation and reinforcement learning.
- ▶ Evaluation on two TREC datasets and promising results in terms of effectiveness.

Perspectives: Totally skipping the query formulation step and designing retrieval models dealing with NL expressions.

REFERENCES

- [1] Ritter, Alan, Colin Cherry, and William B. Dolan (2011). "Data-driven Response Generation in Social Media"
- [2] Bordes, Antoine and Jason Weston (2016). "Learning End-to-End Goal-Oriented Dialog"
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- [4] Song, Hyun-Je, A-Yeong Kim, and Seong-Bae Park (2017). "Translation of Natural Language Query Into Keyword Query Using a RNN Encoder-Decoder"
- [5] Yin, Zi, Keng-hao Chang, and Ruofei Zhang (2017). "DeepProbe: Information Directed Sequence Understanding and Chatbot Design via Recurrent Neural Networks"
- [6] Nogueira, Rodrigo and Kyunghyun Cho (2017). "Task-Oriented Query Reformulation with Reinforcement Learning"