Semi-Supervised QA with Generative Domain-Adaptive Nets

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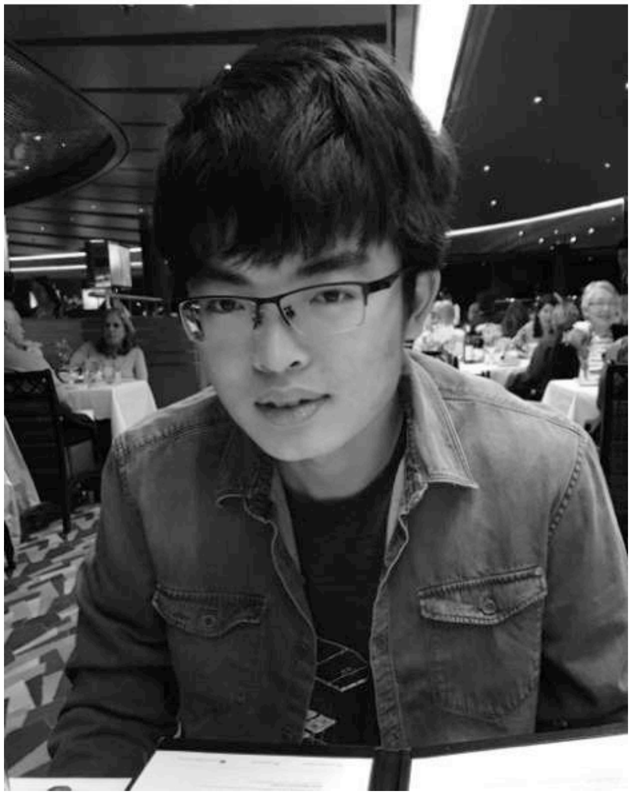
Author



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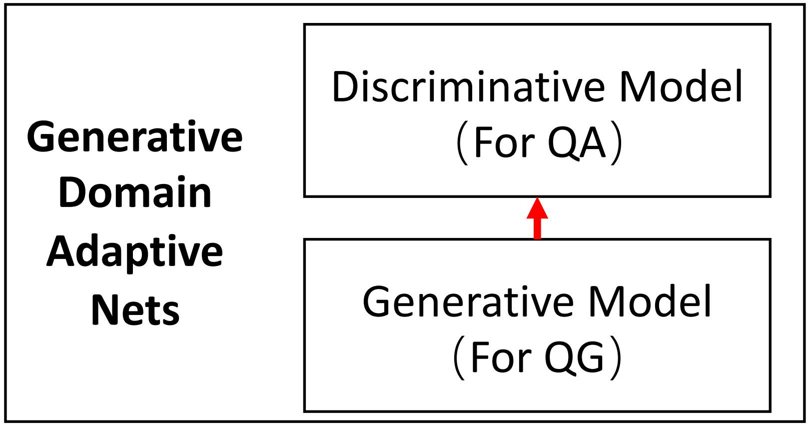
Overview

- **Task**：**Semi-supervised** question answering → *Use unlabeled data*
- **Model**：



1. *Use linguistic tags to extract possible answer*
2. *Train a **generative model** to generate questions*
3. *Train a **discriminative model** based on both data*

- **Problem**： **Discrepancy** between the model-generated data distribution and the human-generated data distribution
- **Method**：**Domain adaptation** algorithms, based on **reinforcement learning （Two domain adaptation techniques）**
  - **Domain tag** （For D） ：model-generated or human-generated
  - **Reinforcement learning** （For G） ：minimize the loss of the discriminative model in an adversarial way

Semi-Supervised QA

1. Dataset：

$$L = \{q^{(i)}, a^{(i)}, p^{(i)}\}_{i=1}^{N}$$

Question： $q^{(i)}$

Answer： $a^{(i)}$

Paragraph： $p^{(i)}$

2. Extractive question answering： where ***a*** is always a consecutive chunk of text in ***p***.

Paragraph: $p = (p_1, p_2, \cdots, p_T)$

Answer: $a = (p_j, p_{j+1}, \cdots, p_{k-1}, p_k)$

Question: $q = (q_1, q_2, \cdots, q_{T'})$

3. Unlabeled Dataset：

$$U = \{a^{(i)}, p^{(i)}\}_{i=1}^{M}$$

4. Question answering mode ***D***

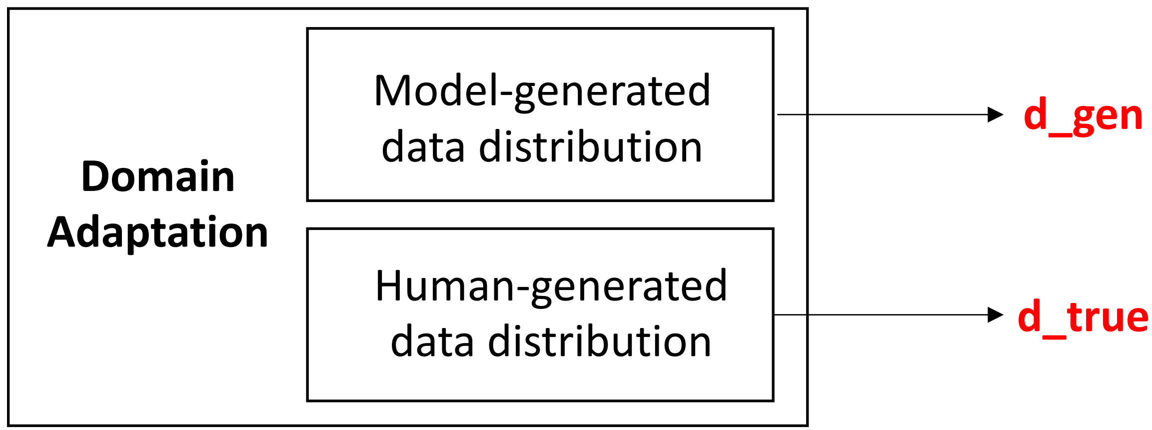
- Discriminative model
- Data: the labeled data ***L*** and the unlabeled data ***U***
- Goal：$\mathbb{P}(a|p, q)$.

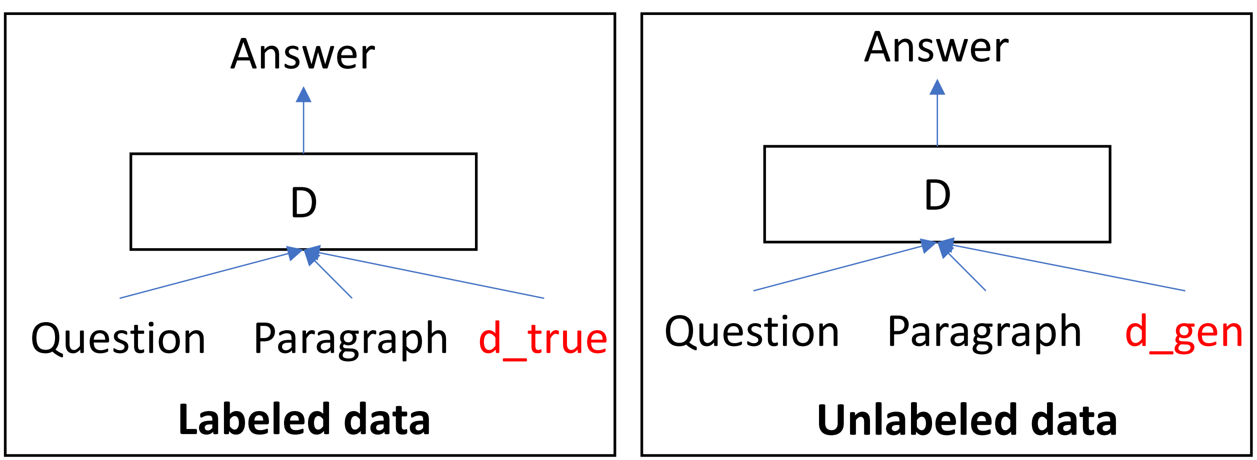
Discriminative Model

- **Goal：** Learns the **Conditional probability** of an answer**(a)** chunk given the paragraph **(p)** and the question (q) $\longrightarrow$ $\mathbb{P}(a|p,q)$.
- **Base Model: Gated-attention (GA) reader**
  - The GA model consists of K layers.
  - $\mathbf{H}_p^k$ be the intermediate paragraph representation at layer k, $\mathbf{H}_p^k$ is a $T \times d$ matrix.
  - $\mathbf{H}_q$ be the question representation, $\mathbf{H}_q$ is a $T' \times d$ matrix.
  - Bi-directional Gated Recurrent Unit (GRU) network.
  - The question and paragraph representations are combined with the gated-attention (GA) mechanism:for each paragraph token p_i
    - $\alpha_j = \frac{\exp \mathbf{h}_{q,j}^T \mathbf{h}_{p,i}^{k-1}}{\sum_{j'=1}^{T'} \exp \mathbf{h}_{q,j'}^T \mathbf{h}_{p,i}^{k-1}}$
    - $\mathbf{h}_{p,i}^k = \sum_{j=1}^{T'} \alpha_j \mathbf{h}_{q,j} \odot \mathbf{h}_{p,i}^{k-1}$
    - $\mathbf{h}_{p,i}^k$ is the the the i-th row of $\mathbf{H}_p^k$ and $\mathbf{h}_{q,j}$ is the j-th row of $\mathbf{H}_q$.
  - Apply two softmax layers on top of $\mathbf{H}_p^K$ to predict the start and end indices of a.

Domain Adaptation with Tags

- **Problem:** Learning from both human-generated data and model-generated data can thus lead to a **biased model**.
- **Method:**





*By introducing the domain tags, we expect the discriminative model to factor out **domain-specific** and **domain-invariant** representations.*

Generative Model

- **Goal:** Learns the **Conditional probability** of generating a question(q) given the paragraph(p) and the answer(a) $\longrightarrow$ $\mathbb{P}(q|p,a)$
- **Base Model:**
  - **sequence-to-sequence** model with **copy** and **attention** mechanism
- **Encoder:**
  - Encodes the input **paragraph** into a sequence of hidden states ***H***
  - Inject the **answer** information by **appending an additional zero/one feature** to the word embeddings of the paragraph tokens
- **Decoder:**

$$\mathbf{p}_{\text{overall}} = g_t \mathbf{p}_{\text{vocab}} + (1 - g_t)\, \mathbf{p}_{\text{copy}}$$

probability of generating the token from the **vocabulary**

probability of copying a token from the **paragraph**

$$g_t = \sigma\left(\mathbf{w}_g^T \mathbf{h}_t\right)$$

Objective function

- **D**：Relies on the data generated by the generative mode
- **G**：Aims to match the model-generated data distribution with the human-generated data distribution using the signals from the discriminative model.
- **D objective function** （*conditioning on domain tags*）

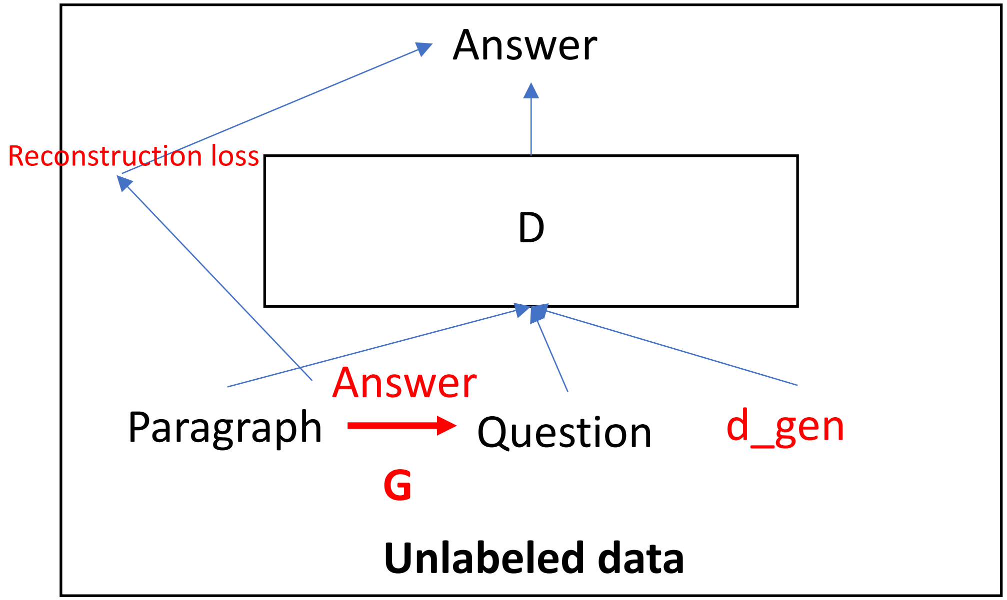
$$J(L, \mathrm{tag}, D) = \frac{1}{|L|} \sum_{p^{(i)}, q^{(i)}, a^{(i)} \in L} \log \mathbb{P}_{D,\mathrm{tag}}(a^{(i)} | p^{(i)}, q^{(i)})$$

- **Final D objective function** ：

$$J(L, \mathrm{d\_true}, D) + J(U_G, \mathrm{d\_gen}, D).$$

Objective function

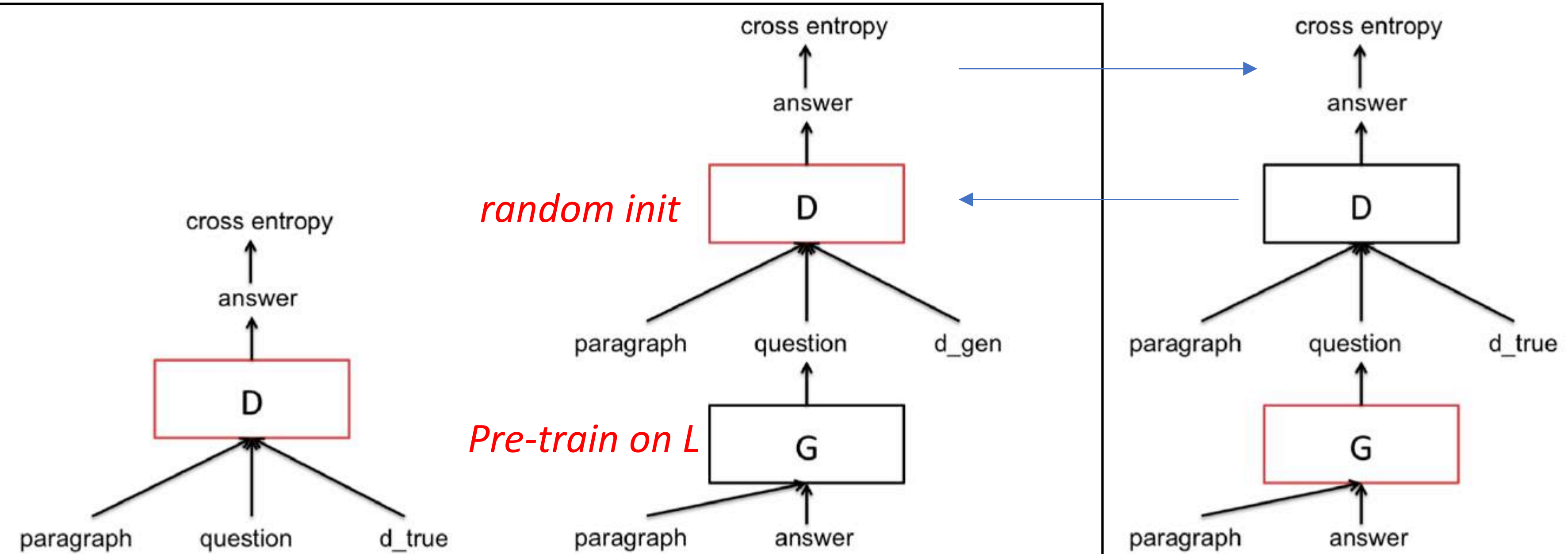
- For G, What will happen if we maxing $J(U_G, \text{d\_gen}, D)$. ?
  - G aims to generate questions that can be reconstructed by the D



  - Generated question maybe the same as the answer!!!
  - Similar to Auto-encoder
- **Method**: **adversarial training objective** $\hat{J}(\hat{U}_G, \boxed{\text{d\_true},} D)$.

Training Algorithm

$\max_D \quad J(L, \text{d\_true}, D) + J(U_G, \text{d\_gen}, D)$ $\quad\quad$ $\max_G \quad J(U_G, \text{d\_true}, D)$

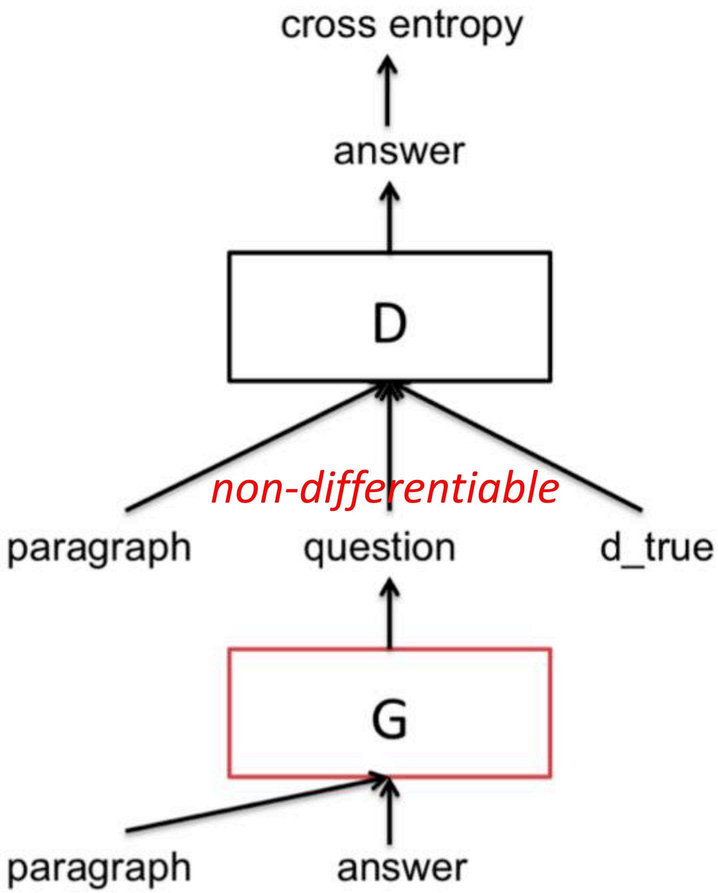


(a) Training the discriminative model on labeled data.

(b) Training the discriminative model on unlabeled data.

(c) Training the generative model on unlabeled data.

Training Algorithm



Reinforcement Learning

- **Action space**：all possible questions with length T （*maybe padding*）
- **Reward**： $J(U_G, \text{d\_true}, D)$
- **Gradient**：

$$\frac{\partial J(U_G, \text{d\_true}, D)}{\partial \theta_G}$$

$$= \mathbb{E}_{\mathbb{P}_G(q|p,a)}(\log \mathbb{P}_{D,\text{d\_true}}(a|p,q) - b)\frac{\partial \log \mathbb{P}_G(q|p,a)}{\partial \theta_G}$$

Experiment -Answer Extraction

- **Assumes: answers are available for unlabeled data**
- Answers in the SQuAD dataset can be categorized into **ten types**, i.e., “Date”, “Other Numeric”, “Person”, “Location”, “Other Entity”, “Common Noun Phrase”, “Adjective Phrase”, “Verb Phrase”, “Clause” and “Other”
    - **Part-Of-Speech (POS) tagger:** label each word
    - **Constituency parser**: **noun phrase, verb phrase, adjective and clause**
    - **Named Entity Recognizer (NER)**： **assign each word with one of the seven labels, “Date”, “Money”, “Percent”, “location”, “Organization” and “Time”.**
- Subsample **five answers** from all the extracted answers for each paragraph according to the percentage of answer types in the SQuAD dataset.

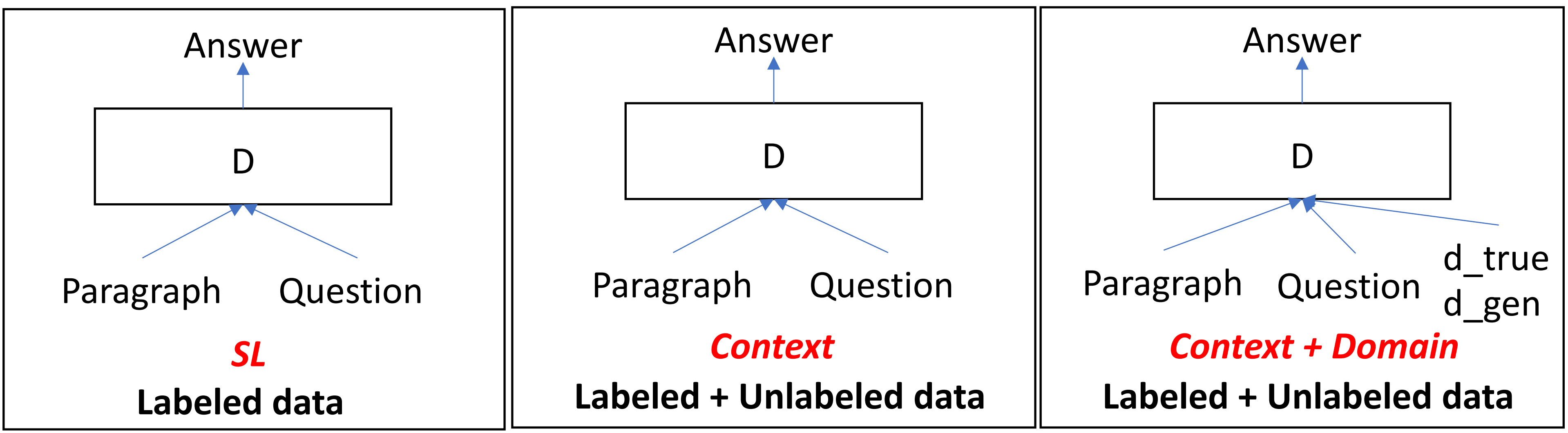
Experiment - Baseline model

- **Given** $p = (p_1, p_2, \cdots, p_T)$
- **Given** $a = (p_j, p_{j+1}, \cdots, p_{k-1}, p_k),$
- **Q:** $(p_{j-W}, p_{j-W+1}, \cdots, p_{j-1}, p_{k+1}, p_{k+2}, p_{k+W})$
  - **W: window size**

Experiment- Comparison Methods

- Methods

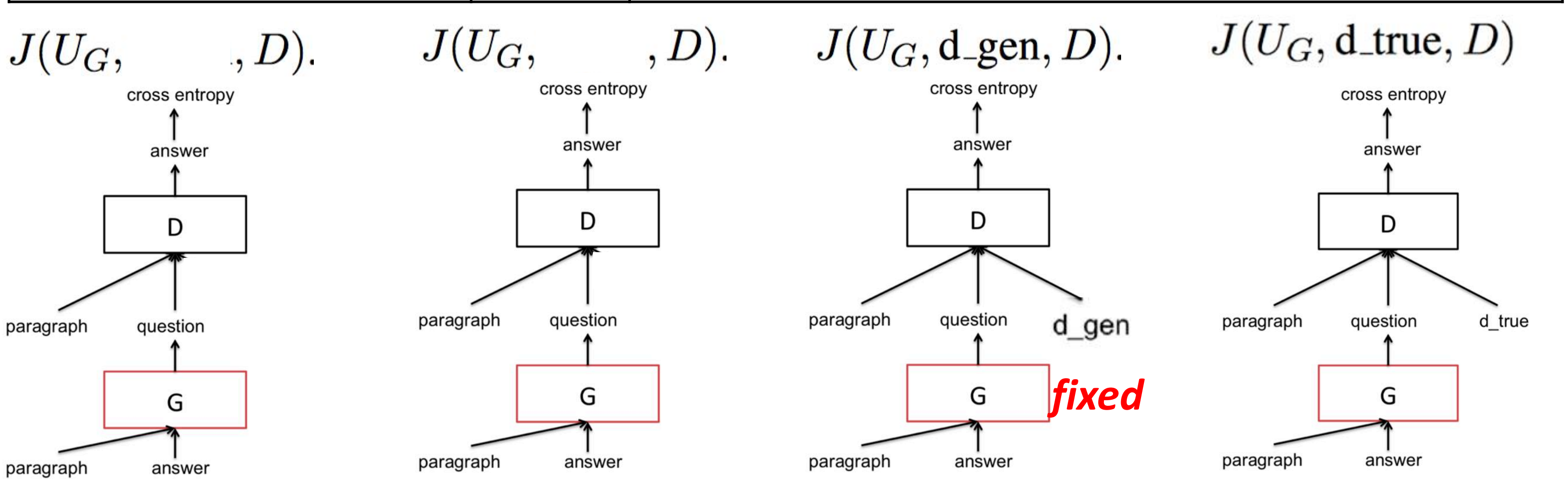
Method	Model	Description
SL	D	supervised learning setting, train the model D on the labeled data L
Context		simple context-based method(baseline model)
Context + domain		Context method with domain tags



Experiment- Comparison Methods

- Methods

Method	Model	Description
Gen	D+G	train a generative model and use the generated questions as additional training data **(copy+attn)**
Gen + GAN		Reinforce
Gen + dual		Dual learning method
Gen + domain		**Gen with domain tags**, while the generative model is trained with MLE and **fixed**.
Gen + domain + adv		Adversarial(adv) training based on Reinforce



Gen + GAN **Gen + dual** **Gen + domain** **Gen + domain + adv**

Results and Analysis

- **Labeling rates**
  - percentage of training instances that are used to train *D*
- **Unlabeled dataset sizes:**
  - sample a subset of around 50,000 instances
- **Metric**
  - F1 score
  - Exact matching (EM) scores

Results and Analysis

- **SL v.s. SSL**
  - use only 0.1 training instances to obtain even better performance than a supervised learning approach with 0.2 training instances

Labeling rate	$\|U\|$	Method	Dev F1	Test F1	Test EM
0.1	50K	Gen + domain + adv	**0.5313**	**0.4802**	**0.3218**
0.2	50K	SL	0.5134	0.4674	0.3163

- **Ablation Study**
  - both the **domain tags** and the **adversarial training** contribute to the performance of the GDANs

Labeling rate	$\|U\|$	Method	Dev F1	Test F1	Test EM
0.1	50K	Gen	0.5049	0.4553	0.3018
0.1	50K	Gen + domain	0.5234	0.4703	0.3145
0.1	50K	Gen + domain + adv	**0.5313**	**0.4802**	**0.3218**

Results and Analysis

- **Unlabeled Data Size**
  - the performance can be further improved when a larger unlabeled dataset is used

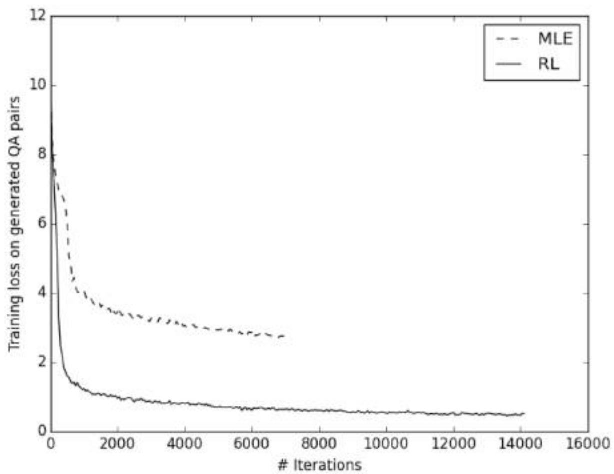
Labeling rate	$\|U\|$	Method	Dev F1	Test F1	Test EM
0.1	50K	SL	0.4262	0.3815	0.2492
0.1	50K	Context	0.5046	0.4515	0.2966
0.1	50K	Context + domain	0.5139	0.4575	0.3036
0.1	50K	Gen	0.5049	0.4553	0.3018
0.1	50K	Gen + GAN	0.4897	0.4373	0.2885
0.1	50K	Gen + dual	0.5036	0.4555	0.3005
0.1	50K	Gen + domain	0.5234	0.4703	0.3145
0.1	50K	Gen + domain + adv	**0.5313**	**0.4802**	**0.3218**
0.1	5M	SL	0.4262	0.3815	0.2492
0.1	5M	Context	0.5140	0.4641	0.3014
0.1	5M	Context + domain	0.5166	0.4599	0.3083
0.1	5M	Gen	0.5099	0.4619	0.3103
0.1	5M	Gen + domain	0.5301	0.4703	0.3227
0.1	5M	Gen + domain + adv	**0.5442**	**0.4840**	**0.3270**

Results and Analysis

- **Context-Based Method**
  - the simple context-based method, though performing worse than GDANs, still leads to substantial gains

Labeling rate	$\|U\|$	Method	Dev F1	Test F1	Test EM
0.1	50K	SL	0.4262	0.3815	0.2492
0.1	50K	Context	0.5046	0.4515	0.2966

- **MLE vs RL**
  - the simple context-based method, though performing worse than GDANs, still leads to substantial gains



Results and Analysis

- **Samples of Generated Questions**
  - RL-generated questions are more informative
  - RL-generated questions are more accurate

P1: is mediated by ige , which triggers degranulation of mast cells and basophils when cross - linked by antigen . type ii hypersensitivity occurs when antibodies bind to antigens on the patient ' s own cells , marking them for destruction . this
A: type ii hypersensitivity
GQ: antibody - dependent hypersensitivity belongs to what class of hypersensitivity ?
Q (MLE): what was the UNK of the patient ' s own cells ?
Q (RL): what occurs when antibodies bind to antigens on the patient ' s own cells by antigen when cross

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P2: an additional warming of the earth ' s surface . they calculate with confidence that co0 has been responsible for over half the enhanced greenhouse effect . they predict that under a " business as usual " (bau) scenario ,
A: over half
GQ: how much of the greenhouse effect is due to carbon dioxide ?
Q (MLE): what is the enhanced greenhouse effect ?
Q (RL): what the enhanced greenhouse effect that co0 been responsible for

Conclusion

- **Task**: Semi-supervised question answering
- **Model**: Generative Domain-Adaptive Nets
- **Simple Baseline method**: Context
- **Experiment**

Thank you!