Augmentation Strategies Optimization for Natural Language Understanding

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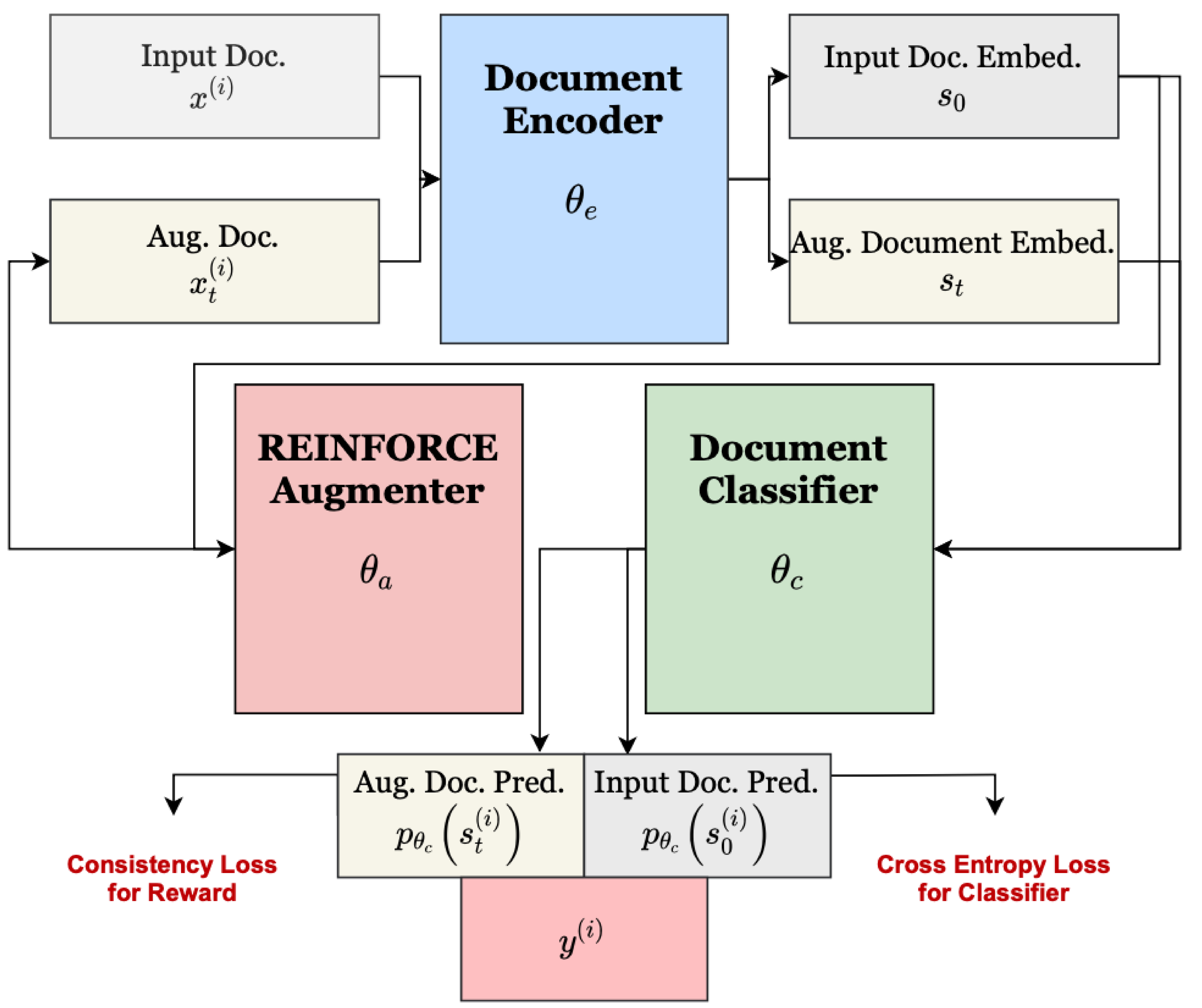
Motivation

- AutoML has successfully introduced automated search process for augmentation strategy to improve model performance in CV tasks.
- Unfortunately, this augmentation strategy method requires high computational cost due to its reward definition.
- Lack of extensive research of augmentation strategy in NLP domain. Most of the previous approach only apply single augmentation method for whole dataset.
- Previous works only apply single augmentation method to the whole dataset, e.g. back-translation.

Automated Data Augmentation for Language Processing and Understanding



Reinforcement Learning Setting

- State: embedded document, $s_t = f\left(x_t^{(i)}; \theta_e\right)$
- Action: five discrete actions

Label: Action	Sentence
0: **RD** (rand delete)	~~**Sparse**~~ only curiously compelling
1: **RS** (rand swap)	**compelling** only curiously **Sparse**
2: **SR** (syn replace)	Sparse only **oddly** compelling
3: **SI** (syn insertion)	Sparse only curiously **oddly** compelling
4: **Stop**	Sparse only curiously compelling

- Reward:
  - $r_t = \begin{cases} \varepsilon, & \text{if } \cos(s_t, s_0) < \alpha \\ \mathrm{JS}(p_{\theta_c}(s_t), p_{\theta_c}(s_0)), & \text{else.} \end{cases}$
  - $\mathrm{JS}\left(p_{\theta_c}(s_t), p_{\theta_c}(s_0)\right) = \frac{1}{2}\left(\mathrm{KL}\left(p_{\theta_c}(s_t) \| \mathcal{M}\right) + \mathrm{KL}\left(p_{\theta_c}(s_0) \| \mathcal{M}\right)\right)$
  - $\mathcal{M} = \frac{1}{2}\left(p_{\theta_c}(s_t) + p_{\theta_c}(s_0)\right)$
  - $r_t \leftarrow r_t - \rho_t$, where $\rho_t = \frac{\bar{r}t}{T}$, $\bar{r}$ t is the average reward, T is the maximum time step.

Algorithm

Algorithm 1: Training for augmentation strategy

Require: $\mathcal{D}$ training dataset. η learning rate
T maximum number of steps
θ_e, θ_a, pars of encoder and augmenter

while θ_a *is not converged* **do**
  for i=*1*, ..., $|\mathcal{D}|$ **do**
    input $x_0^{(i)}$ as i^{th} document in $\mathcal{D}$
    $s_0 = f(x_0^{(i)}; \theta_e)$ as the embedding of $x_0^{(i)}$
    $\{s_0, a_0, r_0, \ldots s_{T-1}, a_{T-1}, r_{T-1}\} \sim \pi_{\theta_a}(\tau)$
    $G_t = \sum_{t'=t+1}^{T} \gamma^{t'-t-1} r_{t'}$
    $g_{\theta_a} \leftarrow \nabla_{\theta_a} \sum_{t=0}^{T-1} \log \pi_{\theta_a}(a_t|s_t) \cdot G_t$
    $\theta_a \leftarrow \theta_a + \eta \cdot \mathrm{Adam}(\theta_a, g_{\theta_a})$

Experiment Results

Table 1: Illustration for the proposed stacked data augmentation (SDA) with five actions (0: random delete, 1: random swap, 2: random synonym replacement, 3: random synonym insertion, 4: stop operation). "x" denotes the failed action due to losing of original semantic meaning, indicated by the condition $\cos(s_t, s_0) < \alpha$. The order of actions and the received reward are shown.

Original Document	Augmented Document	Action	Reward
The name says it all.	The name pronounce it totally	2 2 0 4	0.0484
A lovely and beautifully photographed romance.	A take shoot photograph and lovely beautifully	3 1 2 0 3 4	0.0091
Rouge is less about a superficial midlife crisis than it is about the need to stay in touch with your own skin, at 18 or 80.	with skin. it than less about at or your the ain superficial is midlife crisis, stay need sense of touch touch contain is in about to Rouge vitamin a 18	1 2 2 3 2 3 0 2 3 1 x	0.0049

Table 2: (left) Distribution of actions taken by the policy. **Sim.Thr.** stands for similarity threshold. **Stop** indicates the successfully augmented document without exceeding the max step T or violating the similarity threshold α. (right) Accuracy (%) on different classification tasks. The results from reference papers are shown. "-" denotes the missing results. Augmentation methods using EDA , and back-translation (Back) are compared with SDA. pre-trained model using RoBERTa is merged.

Sim.Thr.	0.7	0.8	0.9
Delete	8.3%	3.8%	3.7%
Swap	0.8%	4.9%	8.0%
Replace	39.8%	22.4%	**67.2%**
Insert	**51.1%**	**68.6%**	20.8%
Stop	7.5%	20.8%	29.1%

Model	SST-2	SST-5	CR	MPQA	Subj	TREC
EFL	**96.9**	-	92.5	90.8	97.1	-
byte mLSTM	91.7	54.6	90.6	88.8	94.7	90.4
BERT	93.1	55.5	-	-	**97.3**	96.8
RoBERTa	94.8	56.6	93.2	90.4	96.0	96.8
RoBERTa with EDA	94.6	56.9	93.3	90.0	95.3	96.6
RoBERTa with Back	95.0	57.3	94.1	90.9	96.9	**97.4**
RoBERTa with SDA	95.2	**58.6**	**94.7**	**91.4**	96.0	97.0