# Data Selection for Supervised Dialogue Generation

Yahui Liu

Tencent AI Lab

yahui.cvrs@gmail.com

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# Self-paced learning

## Self-Paced Curriculum Learning<sup>1</sup>

MentorNet: Regularizing Very Deep Neural Networks on Corrupted Labels<sup>2</sup>

$$\min_{\boldsymbol{\theta}, \mathbf{v} \in [0,1]^n} \mathbb{F}(\boldsymbol{\theta}, \mathbf{v}) = \frac{1}{n} \sum_{i=1}^n \nu_i \mathcal{L}(\mathbf{y}_i, G_{\boldsymbol{\theta}}(\mathbf{x}_i))$$
 (1)

<sup>&</sup>lt;sup>1</sup> Jiang L. et al. Self-Paced Curriculum Learning, AAAI 2015

<sup>2</sup> Jiang L. et al. MentorNet: Regularizing Very Deep Neural Networks on Corrupted Label∰arXiv 2017 ∢ 🧵 ▶

# Curriculum Learning

## Insights

learning principle underlying the cognitive process of humans and animals, which generally start with learning easier aspects of a task, and then gradually take more complex examples into consideration.

#### Curriculum

determines a sequence of training samples which essentially corresponds to a list of samples ranked in ascending order of learning difficulty.

### Key

find a ranking function that assigns learning priorities to training samples.

# Curriculum Learning

## Curriculum Learning (CL)

The curriculum is assumed to be given by an oracle beforehand, and remains fixed thereafter.

- flexible to incorporate prior knowledge from various sources,
- the curriculum is predetermined a priori and cannot be adjusted accordingly, taking into account the feedback about the learner.

## Self-Paced Learning (SPL)

- dynamically generated by the learner itself,
- a concise biconvex problem, ignoring prior knowledge.

# **SPL**

$$\min_{\boldsymbol{\theta}, \mathbf{v} \in [0,1]^n} \mathbb{F}(\boldsymbol{\theta}, \mathbf{v}) = \frac{1}{n} \sum_{i=1}^n v_i \mathcal{L}(\mathbf{y}_i, G_{\boldsymbol{\theta}}(\mathbf{x}_i)) + \lambda \sum_{i=1}^n v_i$$
 (2)

#### Alternative Convex Search

a block of variables are optimized while keeping the other block fixed.

- (1) updating  $\mathbf{v}$  with a fixed  $\boldsymbol{\theta}$ , a sample whose loss is smaller than a certain threshold  $\lambda$  is taken as an "easy" sample;
- (2) when updating  $\theta$  with a fixed  $\mathbf{v}$ , the classifier is trained only on the selected "easy" samples.



# Self-paced Curriculum Learning (SPCL)

#### instructor-student collaborative

$$\min_{\boldsymbol{\theta}, \mathbf{v} \in [0,1]^n} \mathbb{F}(\boldsymbol{\theta}, \mathbf{v}) = \frac{1}{n} \sum_{i=1}^n v_i \mathcal{L}(\mathbf{y}_i, G_{\boldsymbol{\theta}}(\mathbf{x}_i)) + f(\mathbf{v}; \lambda), \text{ s.t. } \mathbf{v} \in \Psi$$
 (3)

Given a predetermined curriculum  $\gamma(\cdot)$  on training samples  $\mathbf{X} = \{\mathbf{x}_i\}_{i=1}^n$  and their weights variable  $\mathbf{v} = [v_1, \cdots, v_n]^T$ . A feasible region  $\Psi$  is called a curriculum region of  $\gamma$  if:

- Soundness:  $\Psi$  is a nonempty convex set;
- Rule: if  $\gamma(\mathbf{x}_i) < \gamma(\mathbf{x}_j)$ , it holds that  $\int_{\Psi} v_i d\mathbf{v} > \int_{\Psi} v_j d\mathbf{v}$ , where  $\gamma(\mathbf{x}_i)$  calculates the expectation of  $v_i$  within  $\Psi$ .

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## **SPCL**

#### Self-Paced Function

- (1)  $f(\mathbf{v}; \lambda)$  is convex with respect to  $\mathbf{v} \in [0, 1]^n$ ;
- (2) When all variables are fixed except for  $v_i, \ell_i, v_i^*$  decreases with  $l_i$ , and it holds that  $\lim_{\ell_i \to 0} v_i^* = 1$ ,  $\lim_{\ell_i \to \infty} v_i^* = 0$ ;
- (3)  $\|\mathbf{v}\|_1 = \sum_{i=1}^n v_i$  increases with respect to  $\lambda$ , and it holds that  $\forall i \in [1, n], \lim_{\lambda \to 0} v_i^* = 0, \lim_{\lambda \to \infty} v_i^* = 1;$

where  $\mathbf{v}^* = \arg\min_{\mathbf{v} \in [0,1]^n} \sum v_i \ell_i + f(\mathbf{v}; \lambda)$ .

# Algorithm & Implementation

## Algorithm

#### Algorithm 1: Self-paced Curriculum Learning.

 $\begin{tabular}{ll} \textbf{input} &: \textbf{Input} \ \text{dataset} \ \mathcal{D}, \textbf{predetermined curriculum} \\ \gamma, \textbf{self-paced function} \ f \ \text{and a stepsize} \ \mu \\ \textbf{output} : \ \textbf{Model parameter} \ \textbf{w} \\ \end{tabular}$ 

- 1 Derive the curriculum region  $\Psi$  from  $\gamma$ ;
- 2 Initialize  $\mathbf{v}^*$ ,  $\lambda$  in the curriculum region;
- 3 while not converged do
- Update  $\mathbf{w}^* = \arg\min_{\mathbf{w}} \mathbb{E}(\mathbf{w}, \mathbf{v}^*; \lambda, \Psi);$ Update  $\mathbf{v}^* = \arg\min_{\mathbf{v}} \mathbb{E}(\mathbf{w}^*, \mathbf{v}; \lambda, \Psi);$
- 5 Update  $\mathbf{v}^* = \arg \min_{\mathbf{v}} \mathbb{E}(\mathbf{w}^*, \mathbf{v}; \lambda, \Psi);$ 6 **if**  $\lambda$  *is small* **then** increase  $\lambda$  by the stepsize  $\mu$ ;
- 6 If  $\lambda$  is small then increase  $\lambda$  by the stepsize  $\mu$
- s end
- 9 return w\*

#### Implementation

• Binary Scheme:

$$f(\mathbf{v}; \lambda) = -\lambda \|\mathbf{v}\|_1 = -\lambda \sum_{i=1}^n v_i$$

Linear Scheme:

$$f(\mathbf{v}; \lambda) = \frac{1}{2} \lambda \sum_{i=1}^{n} (v_i^2 - 2v_i);$$

• Logarithmic Scheme:

$$f(\mathbf{v};\lambda) = \sum_{i=1}^{n} \zeta v_i - \frac{\zeta^{v_i}}{\log \zeta};$$

Mixture Scheme:

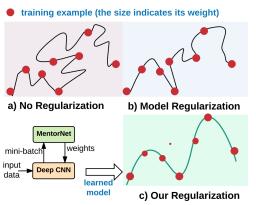
$$f(\mathbf{v}; \lambda) = -\zeta \sum_{i=1}^{n} \log(v_i + \frac{1}{\lambda_1}\zeta).$$

# Comparison

|                              | CL                 | SPL                | Proposed SPCL                        |
|------------------------------|--------------------|--------------------|--------------------------------------|
| Comparable to human learning | Instructor-driven  | Student-driven     | Instructor-student collaborative     |
| Curriculum design            | Prior knowledge    | Learning objective | Learning objective + prior knowledge |
| Learning schemes             | Multiple           | Single             | Multiple                             |
| Iterative training           | Heuristic approach | Gradient-based     | Gradient-based                       |

#### Motivation

Deep models are trained on big data where labels are often noisy, the ability to overfitting noise can lead to poor performance.



#### Formulation

$$\min_{\mathbf{w} \in \mathbb{R}^d, \mathbf{v} \in [0,1]^{n \times m}} \mathbb{F}(\mathbf{w}, \mathbf{v}) = \frac{1}{n} \sum_{i=1}^n \mathbf{v}_i^T \mathcal{L}(\mathbf{y}_i, g_s(\mathbf{x}_i, \mathbf{w})) + G(\mathbf{v}; \lambda) + \theta \|\mathbf{w}\|_2$$
 (4)

#### **Bottleneck**

- minimizing w when fitting v, stochastic gradient descent often takes many steps before converging;
- minimizing v when fitting w, fixed vector v may not even fit into memory.

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#### **Algorithm 1.** SPADE Alg. for optimizing Eq. (1)

**Input**: Input dataset  $\mathcal{D}$ , an explicit regularizer G or a function  $q_m$ .

Output: Model parameters w of the StudentNet.

1 Initialize 
$$\mathbf{w}^{(0)}, \mathbf{v}^{(0)}, \theta^{(0)}, \ell_{pt}^{(0)}, t = 0$$

2 while Not Converged do

Fetch a mini-batch 
$$\Xi_t$$
 uniformly at random;

Compute the loss 
$$\ell$$
 for  $\Xi_t$  and its percentile  $\ell_{pt}^{(t)}$ ;

$$\ell_{pt}^{(t)} = (1 - \gamma)\ell_{pt}^{(t-1)} + \gamma\ell_{pt}^{(t)};$$

$$\mathbf{v}_{\Xi}^{(t)} = \mathbf{v}_{\Xi}^{(t-1)} - \alpha_t \nabla_{\mathbf{v}} \mathbb{F}(\mathbf{w}^{(t-1)}, \mathbf{v}^{(t-1)}) |_{\Xi_t};$$

7 else Update 
$$\mathbf{v}_{\Xi}^{(t)} = g_m(\Xi_t, \mathbf{w}^{(t-1)})$$
;

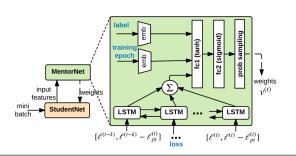
$$\theta^{(t)} = \theta^{(0)} \frac{1}{k} \sum_{i=1}^{k} \mathbf{v}_{\Xi_i}^{(t)};$$

9 
$$\mathbf{w}^{(t)} = \mathbf{w}^{(t-1)} - \alpha_t \nabla_{\mathbf{w}} \mathbb{F}(\mathbf{w}^{(t-1)}, \mathbf{v}^{(t)})|_{\Xi_t};$$

11 end

12 return  $\mathbf{w}^{(t)}$ 

#### Architecture



The parameters of MentorNet and StudentNet are not learned jointly to avoid a trivial solution of producing zero weights for all examples.

### Pretraining

a pretraining dataset  $\mathcal{D}_{pre} = \{(\mathbf{z}_i, v_i^*)\}_i$ , where  $\mathbf{z}_i$  the *i*-th input feature about loss, label and training epoch, and  $v_i^* \in [0,1]$  is a desirable weight. If explicit regularizer G is known:

$$\arg\min_{\Theta} \sum_{\mathbf{z}_i \in \mathcal{D}_{pre}} g_m(\mathbf{z}_i; \Theta) \ell_i + G(g_m(\mathbf{z}_i; \Theta); \lambda)$$
 (5)

Otherwise:

$$\arg\min_{\Theta} \sum_{\mathbf{z}_i \in \mathcal{D}_{pre}} \| v_i^* - g_m(\mathbf{z}_i; \Theta) \|_2^2$$
 (6)

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a third dataset  $\mathcal{D}_{ft} = \{(\mathbf{x}_i, \mathbf{y}_i, v_i^*)\}$ ,  $v_i$  is a binary label indicating whether this example should be learned.

#### Fine-tuning

Mixture of Experts:

For each  $(\mathbf{x}_i, \mathbf{y}_i)$  in  $\mathcal{D}_{ft}$  we first compute its input features  $\mathbf{z}_i$ . Denote  $\mathbf{g}_{\mathbf{k}}(\mathbf{z}_i) = [g_1(\mathbf{z}_i), \cdots, g_k(\mathbf{z}_i)]$  the weights obtained by k pretrained MentorNet  $g_1, \cdots, g_k$ .

$$\arg \min_{\Theta, \mathbf{w_g}} \sum_{v_i \in \mathcal{D}_{ft}} v_i^* \log(G_{\sigma}(\mathbf{w_g}^T \mathbf{g_k}(\mathbf{z}_i) + \epsilon)) \\
+ (1 - v_i^*) \log(1 - G_{\sigma}(\mathbf{w_g}^T \mathbf{g_k}(\mathbf{z}_i) + \epsilon))$$
(7)

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#### Summerization

- Data selection/regularization is an useful tool for supervised learning models.
- Our reweighting methods only depends on prior knowledge, which can be improved in a SPCL method.

# Thanks!