Lecture 23 - L2S, SEARNN

Thursday, April 8, 2021 13:30

today
- learning to search
- SEARNN
- SPENs

Learning to search (L2S)

SEARN Hal Daumé's phd thesis

$h_w : \mathcal{X} \to \mathcal{Y}$

$h_w(x) = \underset{y \in \mathcal{Y}}{\text{argmax}}\ s(x, y; w)$] parameterized search procedure

special case of SEARN: learning to do greedy search

split y in ordered list of decisions

$(y_1, y_2, \dots, y_T)$

learn a classifier $\pi_w(\text{feature}(\hat{y}_1, \dots, \hat{y}_{t-1}; x)) = \hat{y}_t$

π_w: classifier "decoding policy"

L2S framework

from $(x^{(i)}, y^{(i)})_{i=1}^n$ and $\ell(\cdot, \cdot)$

learn a good classifier/policy $\pi_{\hat{w}}$ s.t. $\hat{y}_t = \pi_{\hat{w}}(\varphi(\hat{y}_1, \dots \hat{y}_{t-1}; x))$

$h_{\hat{w}}(x) \triangleq (\hat{y}_1, \dots, \hat{y}_T)$ "greedy decoder"

s.t. $\ell(y^{(i)}, h_{\hat{w}}(x^{(i)}))$ is small

⭐ central idea: "reduction" where reduces structured pred. learning problem to problem of cost sensitive classification learning of π_w

method: generate training data for classifier π_w

$(\hat{y}^{(i)}_{\text{context}}, x^{(i)}, \text{cost}(y_{\text{next}}))$

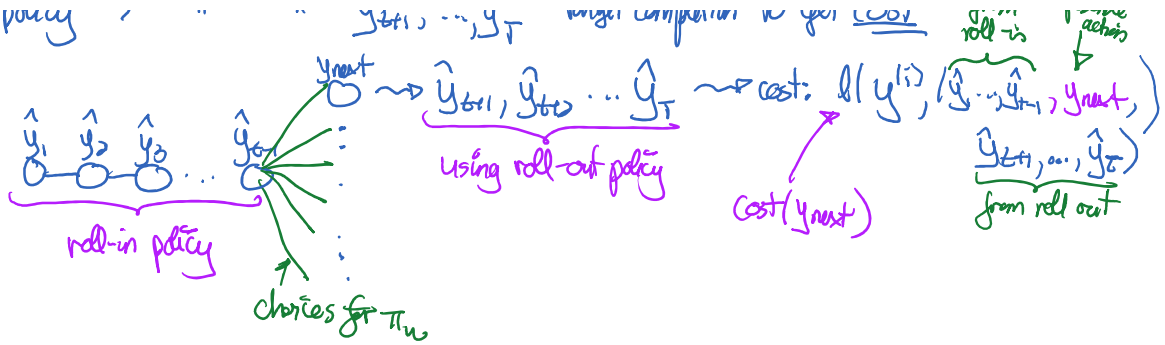
prefix sequence to make next prediction

"roll in" policy → determines how $\hat{y}_{:t-1}$ context

"roll-out" policy → " " $y_{t+1}, \dots, y_T$ "target completion" to get cost

from roll in possible actions

y_{next} → $\hat{y}_{t+1}, \hat{y}_{t+2} \dots \hat{y}_T$ → cost: $\ell(y^{(i)}, (\hat{y}_1 \dots \hat{y}_{t-1}, y_{\text{next}}, \dots))$



"reference policy", ideally, $\pi_{ref}(\hat{y}_1, \dots, \hat{y}_{t-1}, y_{next})$

$= \underset{y_{completion}}{\operatorname{argmin}} \ \ell(y^{(i)}, (\hat{y}_{1:t-1}, y_{next}, y_{completion}))$

intractable (NP hard) in general

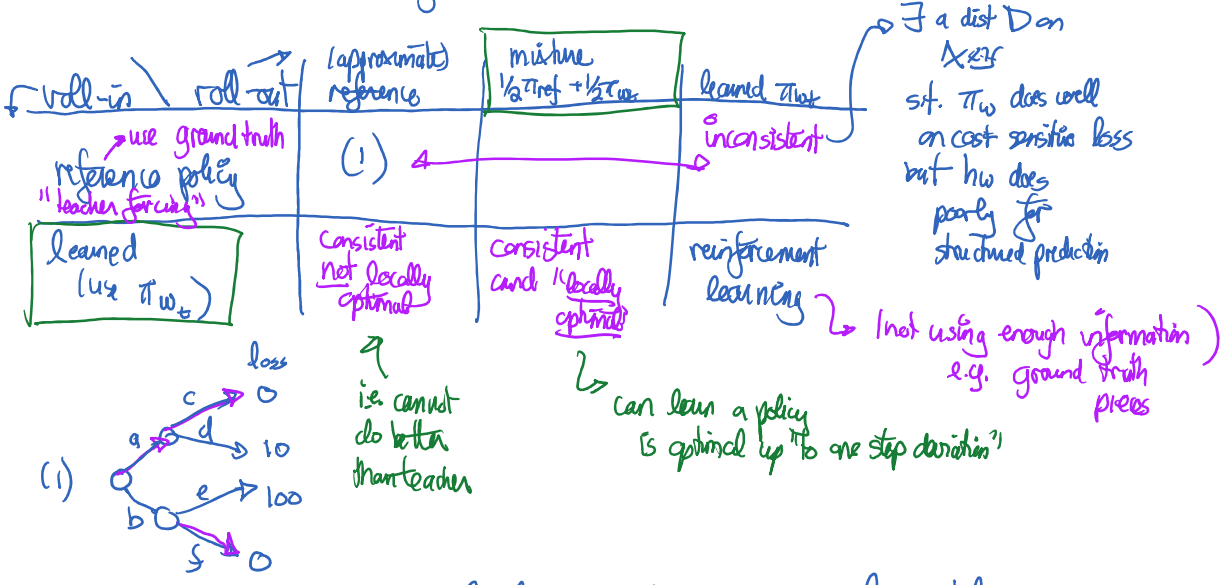
in practice: use heuristic to approximate π

but sometimes, can compute exactly

e.g. π_{ref} for Hamming loss: is just copy ground truth

LOLS → "locally optimal learning to search"

ICML 2015 "LOLS better than your teacher"



example of approximate π_{ref} (in machine translation): ℓ is bleu score

consider all possible suffixes from ground truth and pick the best bleu score one

14h28

SEARNN : apply L2S to RNN training

[Leblond & al. ICLR 2018] i.e. $\pi_w(y_{1:t-1}, x) \rightsquigarrow$ RNN cell

$p(y_{next} \mid y_{1:t-1}, x)$ of a (decoder) RNN

if you use $-\log p(\hat{y}_{target} \mid y_{1:t-1}, x)$ as a cost surrogate

and $\hat{y}_{target}$ = ground truth

then L2S with π_{ref} roll-in is standard MLE

(*) cost-sensitive surrogate losses choices

a) structured SVM : $\max_{y'} [\underbrace{\Delta(y')}_{\triangleq c(y') - c(y_{target})} + s(y')] - s(y_{target})$

$y_{target} \triangleq \operatorname{argmin}_{y'} c(y')$

b) "target log-loss" : $-\log p_{\pi_0}(y_{target} \mid y_{1:t-1}, x)$

↳ differences with MLE :

- address exposure bias using learned roll-in
- make use of structured loss $\Delta(\cdot,\cdot)$ to predict $\hat{y}_{target}$ vs. ground truth in MLE

Structured prediction energy networks (SPENs)

ICML 2016

$E(x, y; w)$ $\quad (-s(x, y; w))$

- relax $y \in \{0,1\}^T \rightsquigarrow [0,1]^T$

$h_w(x)$ = a few steps of projected GD on $E(x, y; w)$ w.r.t. to y (approximate prediction procedure)

+ rounding

2016 paper :

SSVM loss $\rightsquigarrow$ "subgradient" method on w

hinge loss : $\max_{\bar{y} \in [0,1]^T} (\ell(y^{(i)}, \bar{y}) - E(x^{(i)}, \bar{y}; w)) + E(x^{(i)}, y^{(i)}; w)$

requires an extension

$y \in \mathcal{Y}(x^{(i)})$ → requires an extension

approximate "subgradient" is $-\nabla_w E(x^{(i)}, \tilde{y}^*(w_t); w) + \nabla_w E(x^{(i)}, y^{(i)}; w)$

↑ because $\tilde{y}^*$ is approximate max

→ e.g. see Clarke subdifferential for generalization on non-convex fct.

2017 paper: end-to-end learning:

$$h_w(x) = y_0 - \sum_{t=1}^{T} \eta_t \frac{d}{dy} E(x, y_t; w)$$

(recursively defined: y_t) "unrolled optimization"

$$y_1 = y_0 - \eta_1 \frac{d}{dy} E(x, y_0; w)$$

$$y_2 = y_1 - \eta_2 \frac{d}{dy} E(x, y_1; w) \quad \text{etc...}$$