

I label noise 概述

harmful.
 Training: overfit
 Validation: network is overconfident.
 Ubiquitous.
 DN suffers noise to its ability to learn

Task 1.

extract confident example

Memorization effect: prefer major pattern.

During early training stage, examples with small loss are likely to be true.

PES (Pseudo-Example Selection)
 RSA (Robust Self-Adaptation)

Task 2

Semi-supervised.

DivideMix

Task 3.

Label noise learning.

class conditional $P(X|\tilde{y}=j) = \sum_{i=1}^C \alpha_{ij} P(X|\tilde{y}=i)$.

class posterior \star

$P(\tilde{y}=i|X) = \sum_{j=1}^C \beta_{ij} P(\tilde{y}=j|X)$.

1.

Label Noise Algorithm

Stochastically inconsistent algorithm (heuristic).
 Select clean label
 re-weighting
 correcting labels.

SCA: design classifier-consistent algorithms

s.t. converge to classifier on clean domain!!!

SCA:
 clean label transition model: $T(X) = P(\tilde{y}|Y, X=\vec{x})$.

basic math: clean label classifier \rightarrow clean class posterior $P(Y|X)$
 Through learning, $\hat{y}(x) := \arg \max_{\tilde{y}} P(\tilde{y}|X)$.
 clean label distribution.
 通过 T
 noisy label posterior $P(\tilde{y}|X)$.
 classifier learned in real dataset.

So, $N = TC$.

Expected Risk: $R_{D,0-1}(f) = E_{(X,Y) \sim D} [1(f \neq \text{sign}(f(X)))]$

Empirical Risk: $\hat{R}_{D,L}(f) = \frac{1}{n} \sum_{i=1}^n \ell(y_i, f(x_i))$

2. T is determined by the type of NL.
 RCN: instance-independent
 CCN: instance-independent
 IDN: instance-dependent

a. Assume T is predetermined.

① RCN

Thm: As long as $L(f(x), +1) + L(f(x), -1) = C$.

then, $\arg \min_f R_{0,1}(f) = \arg \min_f R_{D,L}(f)$.

because,

$R_{D,L}(f) = E_{(X,\tilde{Y}) \sim \tilde{D}} [L(f(X), \tilde{Y})] = (1-\rho) R_{D,L}(f) + \rho C$

② CCN

Thm: Modify ℓ to be $\hat{\ell}$ that

$E_{(X,\tilde{Y}) \sim \tilde{D}} [\hat{\ell}(f(X), \tilde{Y})] = E_{(X,Y) \sim D} [\ell(f(X), Y)]$.

for binary classification, with the help of T .

Unbiased estimator is derived.

③ IDN

Importance reweighting.

forward correction.

b. how to estimate T ?

$N = TC$ suffers from identifiability ($A = TB = (T\alpha)(\alpha^{-1}B)$).

Known

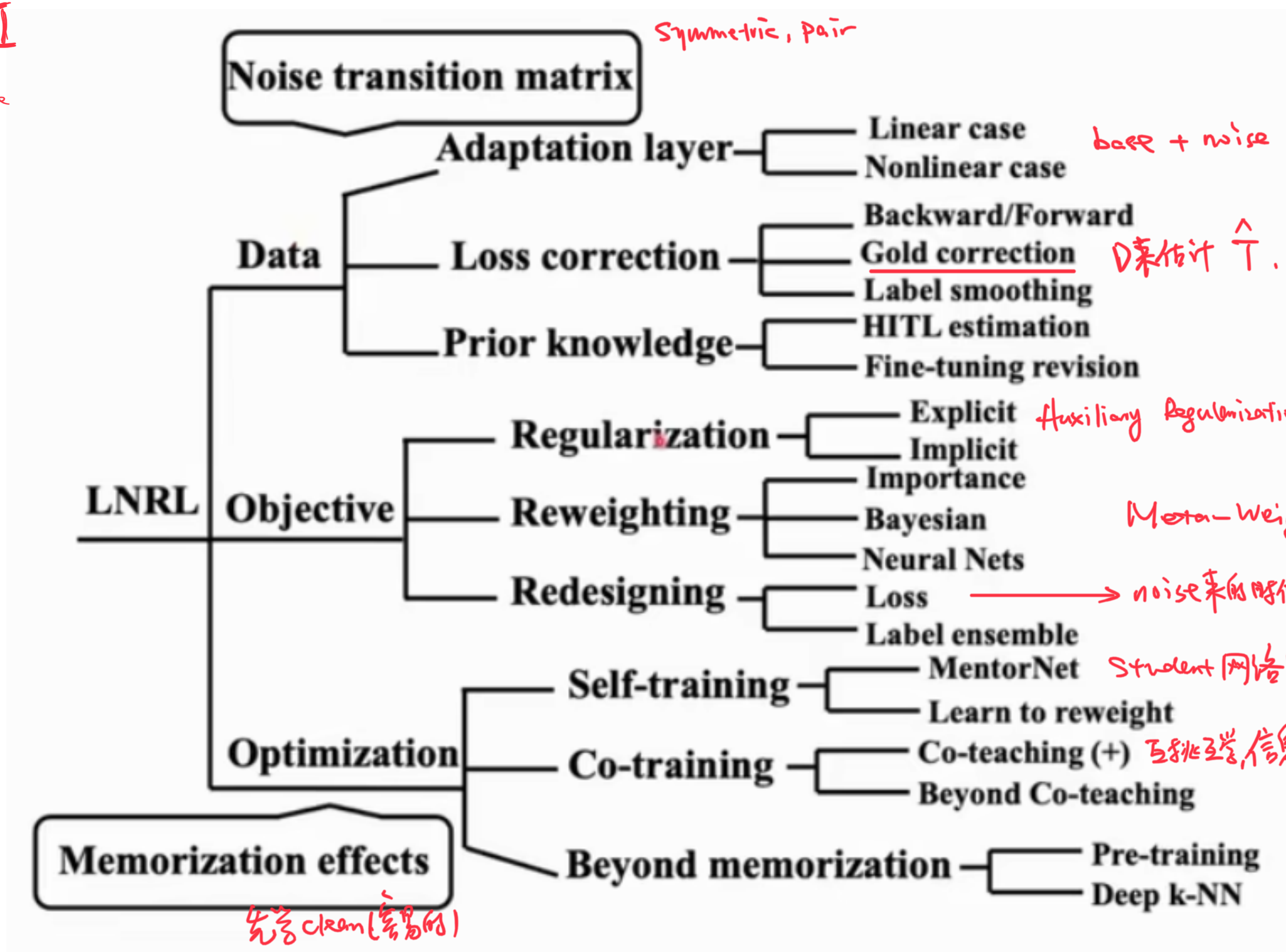
So there has to be prior condition.

instance-independent
 ① anchor point Assm. if ap exists, $P_{Y,\tilde{Y}} = \sum_{\vec{x} \in X} C(\tilde{y} = y | \vec{x})$.
 ② sufficiently scattered Assm.

instance-dependent
 ① part-dependent.
 ...

II

Label Noise
 常用算法分类



Small-loss trick: 只学小loss的样本, 其他淘汰

更强的标签: instance-dependent, OOD noise.