From Noisy Prediction to True Label: Noisy Prediction Calibration via Generative Model

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Learning with Noisy Labels

- Noisy labels are inevitable
  - Large-size dataset is unanimous for the success of DNNs.
  - Yet such large-scale dataset creation is arduous and prone to errors in their label annotations.

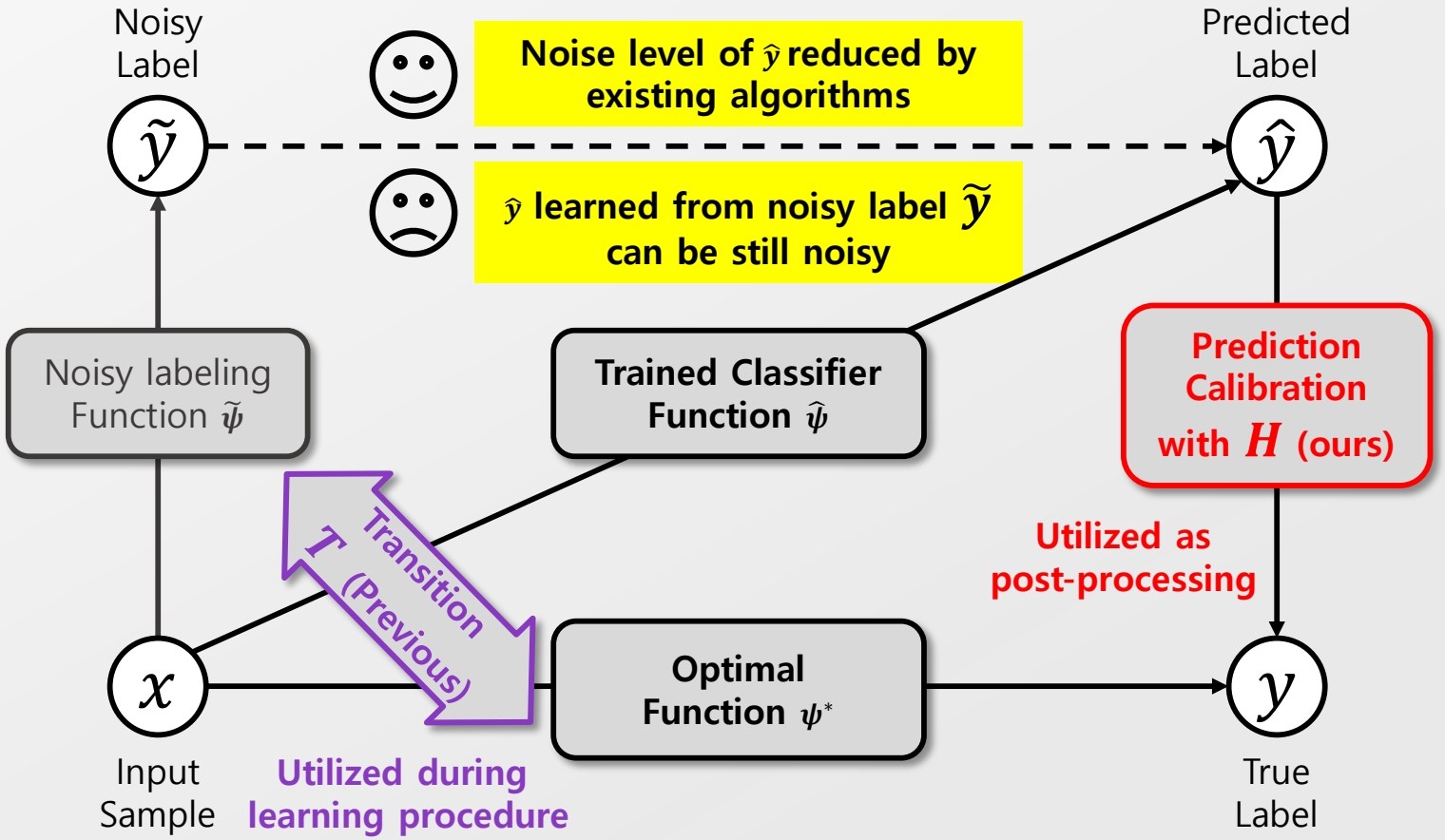
What we get → $\tilde{R}_L^{emp}(f) := \frac{1}{n}\sum_{i=1}^{n} L(f(x_i), \tilde{y}_i)$

What we want → $R_L(f) := E_{(X,Y)\sim P(x,y)}[L(f(x), y)]$

- Existing methods are still not robust to label noises: They should solve two problems simultaneously.
  - Train a classifier
  - Manage noisy label problem

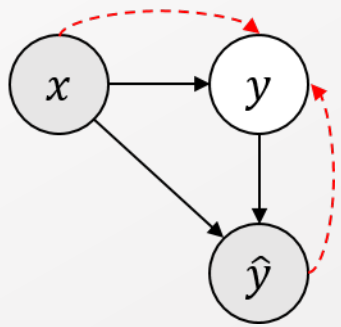
- Modelling of reducing the gap between the prediction of trained classifier and the true latent label is necessary!

Motivation



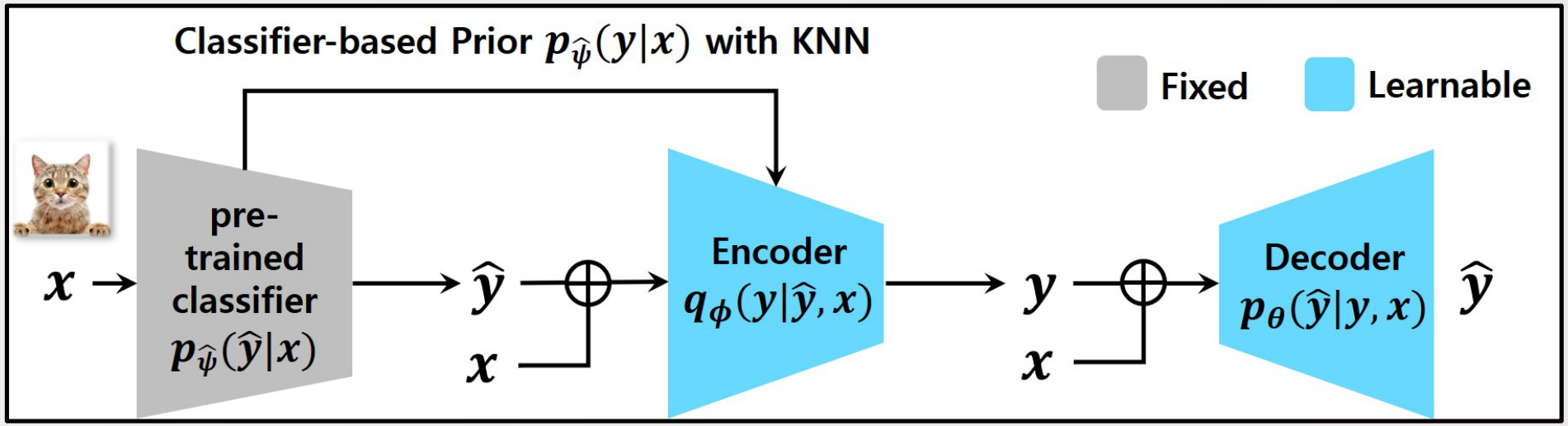
NPC: Noisy Prediction Calibration

- Bayesian Network



- Generative Process
  1. $y \sim Dir(\alpha_x)$
  2. $\tilde{y} \sim Multi(\pi_{x,y})$
- $\mathbf{p}(\boldsymbol{y}|\hat{\boldsymbol{y}}, \boldsymbol{x})$ **is intractable!**
  - → Minimize KL$(q(y|\hat{y}, x)|p(y|\hat{y}, x))$

- Neural Network structure of NPC $\quad p(y|x) = \sum_{\hat{y}} q_\phi(y|\hat{y}, x)\, p_{\hat{\psi}}(\hat{y}|x)$

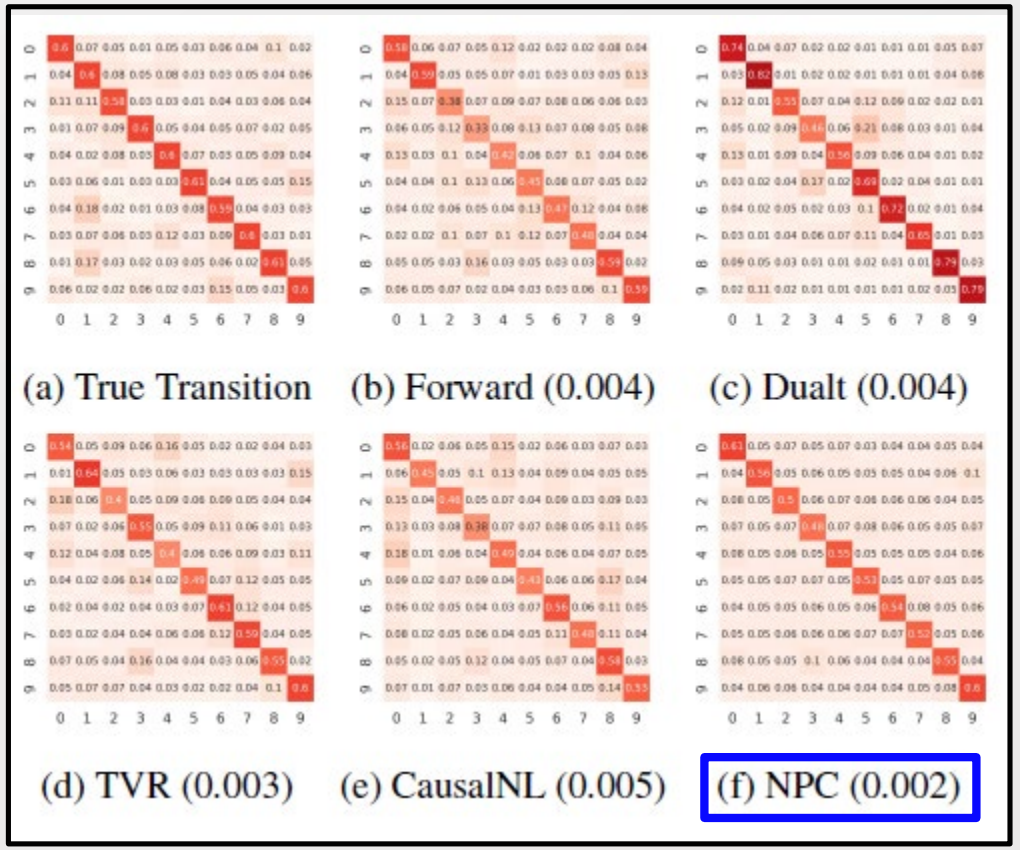


NPC: Noisy Prediction Calibration

- Although NPC works as a post-processing algorithm, H provides a same pathway to correct the noisy classifier as T.

$$H_{kj}(x) = \frac{p(y=j|x)}{p(\hat{y}=k|x)} \sum_i p(\hat{y}=k|\tilde{y}=i,x) T_{ij}(x)$$

- NPC can approximate T good enough.
  - Values in parentheses are the MSE between the estimation and the truth.
  - NPC can also generate the transition matrix with comparable quality.



Experiment Result

- Test accuracy : Synthetic Datasets

Model	MNIST		Fashion-MNIST									CIFAR-10								
	Clean	IDN	Clean	SN		ASN		IDN		SRIDN		Clean	SN		ASN		IDN		SRIDN	
	-	40%	-	20%	80%	20%	40%	20%	40%	20%	40%	-	20%	80%	20%	40%	20%	40%	20%	40%
CE	97.8	66.3	87.1	74.0	27.0	81.0	77.3	68.4	52.1	81.0	67.3	86.9	73.1	15.1	80.2	71.4	72.9	53.9	72.6	61.8
w/ NPC	**98.2**	**89.0**	**88.4**	**84.0**	**35.8**	**85.9**	**86.2**	**82.5**	**74.5**	**81.8**	**69.4**	**89.0**	**80.8**	**17.0**	**84.7**	**78.8**	**80.9**	**59.9**	**74.3**	**64.3**
Joint	93.0	93.6	82.8	82.0	**6.0**	82.1	82.3	82.7	82.4	80.6	74.6	83.0	78.9	**8.3**	81.5	76.8	80.4	64.5	70.6	62.2
w/ NPC	**94.0**	**94.6**	**83.6**	**82.7**	**6.0**	**82.9**	**82.9**	**83.4**	**83.0**	**81.1**	**75.5**	**84.4**	**80.2**	**8.3**	**83.0**	**77.7**	**80.7**	**69.1**	**72.0**	**63.6**
Coteaching	98.0	87.5	87.0	82.5	64.2	88.2	**73.6**	81.8	75.4	84.0	75.0	88.5	82.5	29.7	86.5	76.6	81.5	75.2	75.3	66.6
w/ NPC	**98.3**	**90.6**	**88.3**	**85.8**	**66.0**	**88.5**	**73.6**	**85.1**	**78.7**	**84.2**	**75.3**	**89.2**	**85.3**	**32.1**	**87.1**	**76.8**	**84.8**	**78.5**	**76.1**	**67.2**
JoCoR	97.8	93.3	88.7	86.0	27.6	88.9	79.4	86.3	83.2	81.9	71.3	89.1	83.6	24.8	82.6	73.3	82.8	75.3	75.2	66.1
w/ NPC	**98.3**	**96.1**	**89.8**	**88.0**	**31.5**	**89.2**	**82.7**	**88.0**	**85.7**	**82.2**	**72.3**	**89.3**	**86.0**	**27.0**	**85.1**	**79.0**	**85.8**	**80.1**	**75.9**	**66.7**
CORES2	97.0	48.8	87.2	74.6	8.9	77.6	74.3	80.0	58.1	81.3	71.2	87.1	70.1	**31.2**	79.0	71.2	70.3	50.9	72.8	62.0
w/ NPC	**98.0**	**67.2**	**88.5**	**84.3**	**10.2**	**82.5**	**81.0**	**84.0**	**69.6**	**82.2**	**74.9**	**88.2**	**80.4**	30.7	**84.2**	**80.4**	**80.4**	**65.6**	**74.2**	**64.1**
SCE	97.7	66.6	87.0	74.0	27.0	82.0	77.4	68.3	52.0	81.1	67.5	86.9	73.1	15.1	80.2	71.4	72.9	53.9	72.6	61.8
w/ NPC	**98.2**	**88.7**	**88.3**	**83.7**	**35.5**	**86.4**	**86.7**	**82.0**	**75.2**	**81.8**	**69.7**	**87.4**	**75.0**	**15.2**	**81.5**	**75.2**	**75.4**	**55.6**	**72.9**	**62.5**
Early Stop	96.5	73.3	87.5	83.6	49.5	84.1	76.6	79.5	55.4	83.3	72.6	83.0	79.1	18.0	80.9	70.6	77.1	62.5	71.4	60.6
w/ NPC	**97.9**	**90.8**	**88.7**	**85.9**	**62.9**	**87.6**	**87.1**	**84.3**	**75.3**	**84.0**	**76.0**	**84.0**	**82.5**	**18.2**	**81.2**	**72.0**	**79.4**	**65.1**	**72.1**	**63.0**
LS	97.8	66.2	87.5	73.9	27.8	81.5	77.0	69.0	52.5	81.1	67.5	86.9	73.1	15.1	80.2	71.4	72.9	53.9	72.6	61.8
w/ NPC	**98.2**	**88.6**	**88.6**	**83.7**	**35.2**	**86.0**	**86.4**	**82.2**	**74.7**	**81.6**	**69.5**	**89.0**	**80.8**	**15.5**	**84.7**	**78.8**	**80.9**	**59.9**	**74.3**	**64.3**
REL	**98.0**	90.7	**88.1**	84.6	70.1	82.8	76.2	**84.6**	75.5	**83.7**	78.1	80.7	74.9	21.2	72.8	69.9	75.5	**51.8**	69.3	63.8
w/ NPC	97.9	**95.5**	86.9	**85.0**	**70.3**	**85.3**	**83.0**	83.8	**80.1**	82.9	**78.3**	**83.4**	**78.6**	**26.0**	**75.9**	**76.1**	**78.5**	51.2	**70.7**	**64.2**
Forward	98.0	67.9	88.5	77.4	24.3	83.3	79.2	75.2	56.9	82.4	69.5	85.3	71.8	16.9	78.2	70.1	70.2	54.5	73.2	63.5
w/ NPC	**98.4**	**91.1**	**89.6**	**85.3**	**33.0**	**87.2**	**86.8**	**86.8**	**80.5**	**83.3**	**73.7**	**88.7**	**81.5**	**17.2**	**83.8**	**74.5**	**80.3**	**63.3**	**74.8**	**65.0**
DualT	96.7	94.3	86.3	84.5	**10.0**	86.9	83.1	85.1	68.5	82.7	73.2	84.3	79.3	7.6	80.6	77.1	78.6	71.2	68.7	63.1
w/ NPC	**97.8**	**96.6**	**88.2**	**85.9**	**10.0**	**87.6**	**84.3**	**86.3**	**72.3**	**83.4**	**74.9**	**86.0**	**83.0**	**8.4**	**83.0**	**77.5**	**81.0**	**77.3**	**70.1**	**64.0**
TVR	97.7	64.4	87.0	72.6	24.9	80.6	76.4	66.3	51.7	81.4	67.7	86.7	71.9	15.2	78.5	71.2	72.3	53.6	72.2	62.2
w/ NPC	**98.1**	**84.5**	**88.3**	**82.3**	**31.9**	**84.9**	**85.3**	**79.8**	**73.6**	**82.1**	**70.3**	**88.3**	**80.8**	**15.7**	**84.1**	**76.5**	**80.8**	**60.7**	**74.5**	**64.5**
CausalNL	98.1	85.2	88.1	84.0	51.5	88.8	87.4	83.4	75.2	82.0	71.2	89.6	79.9	17.0	84.6	74.8	79.9	60.4	74.6	63.5
w/ NPC	**98.6**	**94.5**	**89.4**	**87.0**	**58.9**	**89.3**	**88.7**	**87.6**	**83.3**	**83.3**	**74.1**	**89.7**	**81.2**	**18.8**	**85.0**	**74.8**	**81.2**	**71.9**	**75.3**	**63.9**

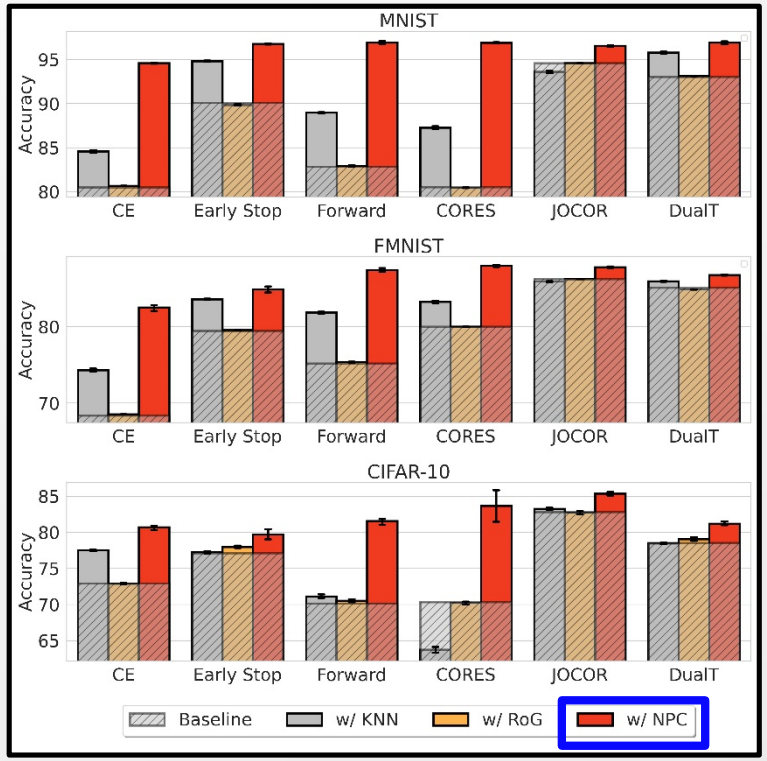
Experiment Result

- Test accuracy : Real Datasets

Method	Food-101		Clothing1M	
	w.o/ NPC	w/ NPC	w.o/ NPC	w/ NPC
CE	78.37	**80.21**±0.2	68.14	**70.83**±0.1
Early Stop	73.22	**76.80**±0.3	67.07	**70.21**±0.1
SCE	75.23	**78.26**±0.3	67.77	**70.36**±0.1
REL	78.96	78.95±0.4	62.53	**64.83**±0.1
Forward	83.76	83.77±0.3	66.86	**70.02**±0.1
DualT	57.46	**61.82**±0.7	70.18	69.99±0.4
TVR	77.34	**79.37**±0.1	67.18	**69.44**±0.1
CausalNL	86.08	**86.29**±0.0	68.31	**69.90**±0.2

Experiment Result

- NPC as a post-processor



- NPC shows the best performances **among post-processors**

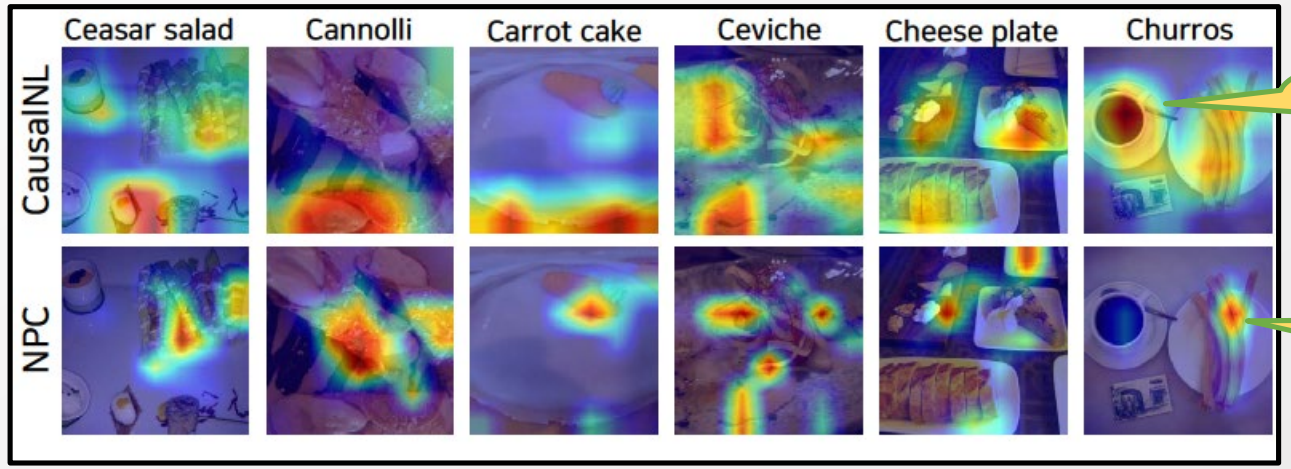
Method	Label Correction			
Noise	Joint	LRT	MLC	CauseNL
SN	80.0±0.6	82.9±0.2	71.1±1.9	77.2±1.5
IDN	78.6±1.3	82.5±0.2	72.2±2.6	78.4±1.7

Method	Post-processing			
Noise	LRT*	MLC*	CauseNL*	NPC
SN	82.7±0.1	82.2±1.9	83.5±0.5	**85.3**±0.3
IDN	82.9±0.2	82.1±0.4	83.3±0.5	**84.8**±0.1

- NPC achieves better accuracy than Label Correction methods
- Asterisks represent label correction to model prediction (application as post-processor)

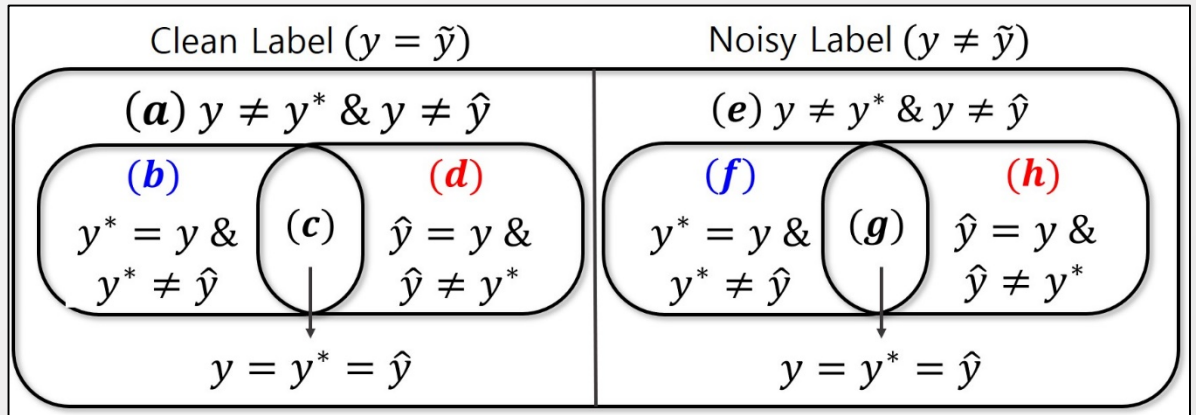
Experiment Result

- NPC as a Generative Model



CausalNL: Total Image

NPC: Class-related

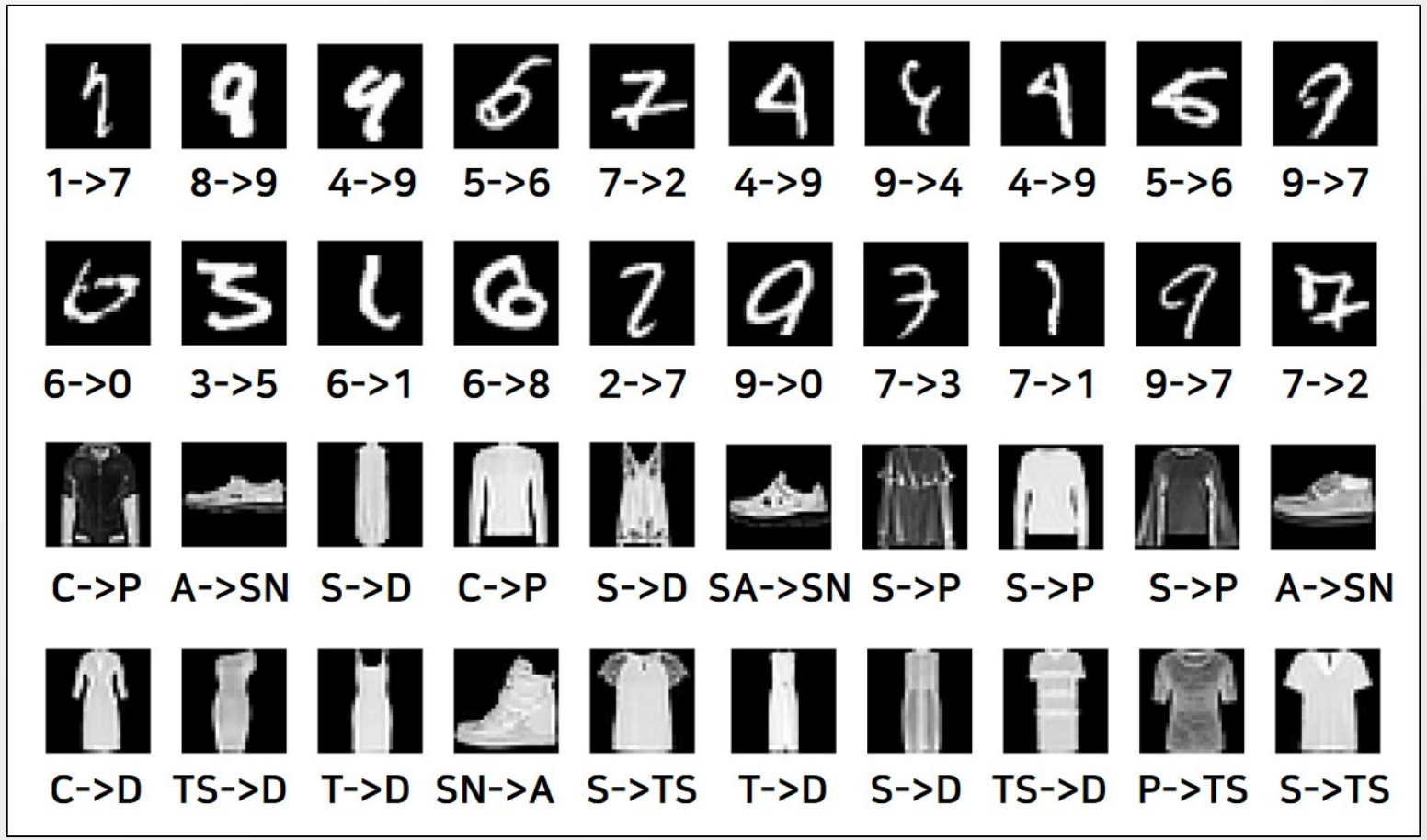


	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
NPC	8	89	39799	86	9035	949	15	19
CausalNL*	39	58	32459	7426	2446	7538	31	3

- A good post processor should increase ☐ and decrease ☐
- NPC a cautious corrector
- CausalNL more risk-taker

Experiment Result

- NPC identifies potential noises in benchmarks



Conclusion

- We introduce novel post-processing method ‘NPC’ (Noisy Prediction Calibration)
  - NPC models the relation between output of a classifier and the true label via generative model.
  - NPC consistently boosts the classification performances of pre-trained models from diverse algorithms.
  - The prediction calibration scheme of NPC can be applied on various fields of machine learning.

Classifier Training (In-Processing)

- Computationally inefficient for models with too many parameters. (e.g. CLIP, GPT-3)
- It often hinge upon heuristics or assumptions (e.g. simple pattern at the early learning)

Prediction Calibration (Post-Processing)

- Model-agnostic algorithm which only requires the model prediction.
- Modeling objective is defined based on true latent label (Y)

Thank you