The Aleatoric Uncertainty Estimation Using a Separate Formulation with Virtual Residuals

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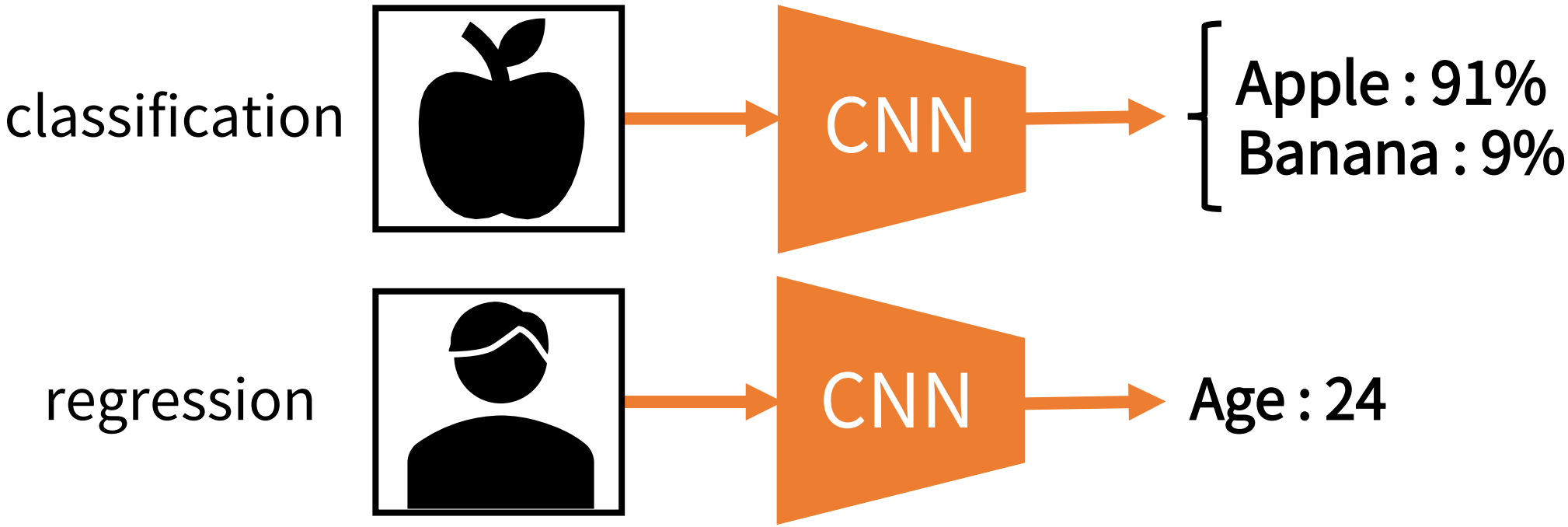
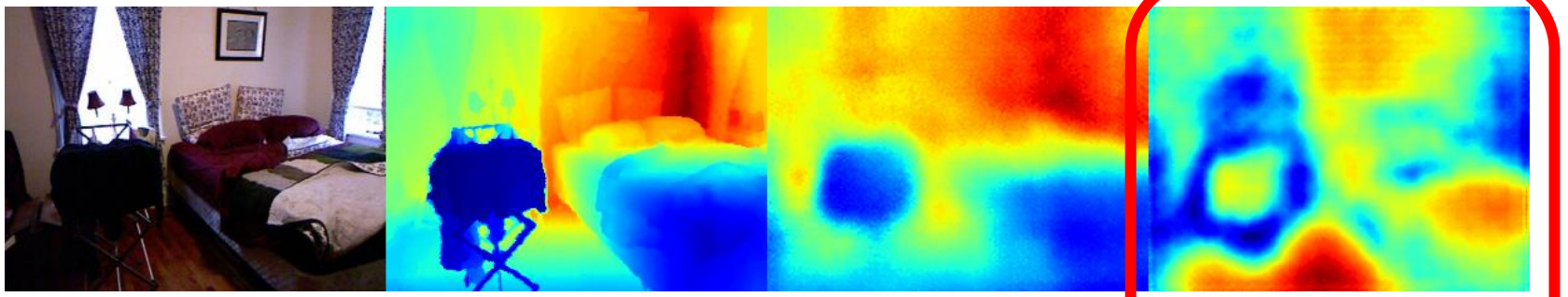
Uncertainty Estimation during Deep Learning

For regression tasks,
confidence of the model output is uncertain.



Uncertainty Estimation during Deep Learning

The confidence of the model output is essential especially in tasks where safety is important such as depth estimations for automatic driving.



[1] N. Silberman, et al. “Indoor segmentation and support inference from rgbd images.”, *ECCV*, 2012.

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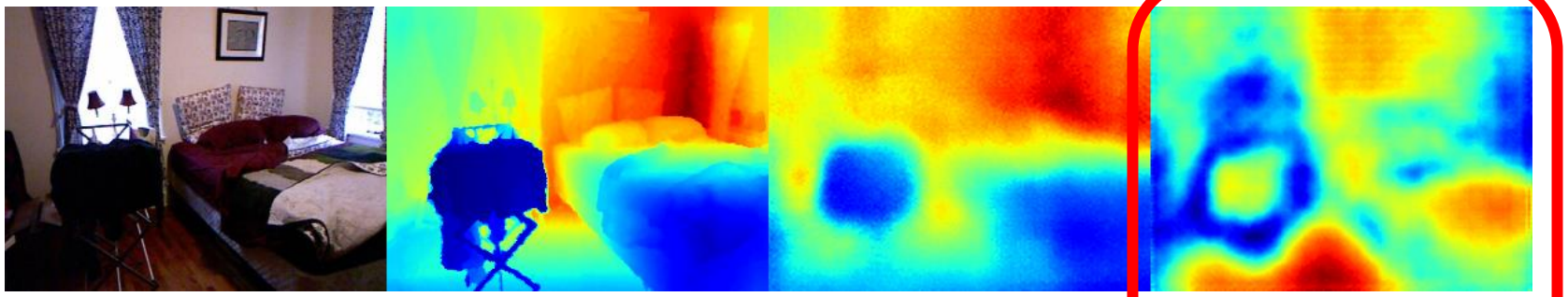


input[1] **depth**[1] **depth estimation** **error (uncertainty)**

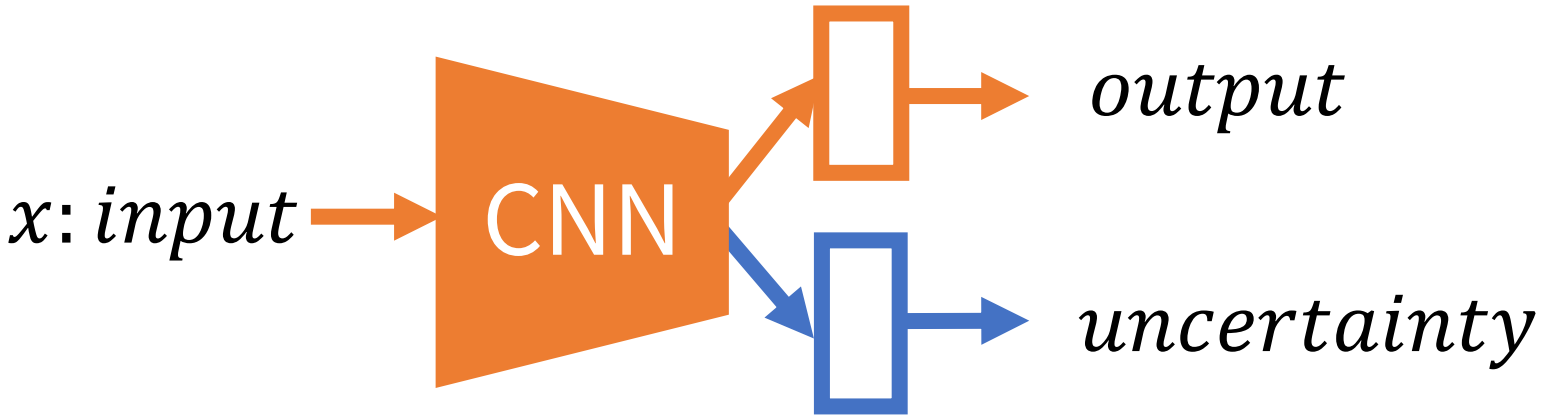
→ We predict aleatoric uncertainty, which is dependent on input.

[1] N. Silberman, et al. “Indoor segmentation and support inference from rgbd images.”, *ECCV*, 2012.

Existing Works for Aleatoric Uncertainty Estimation

Gal[2], Kendall and Gal[3]

Output and estimate both of targets and uncertainties.



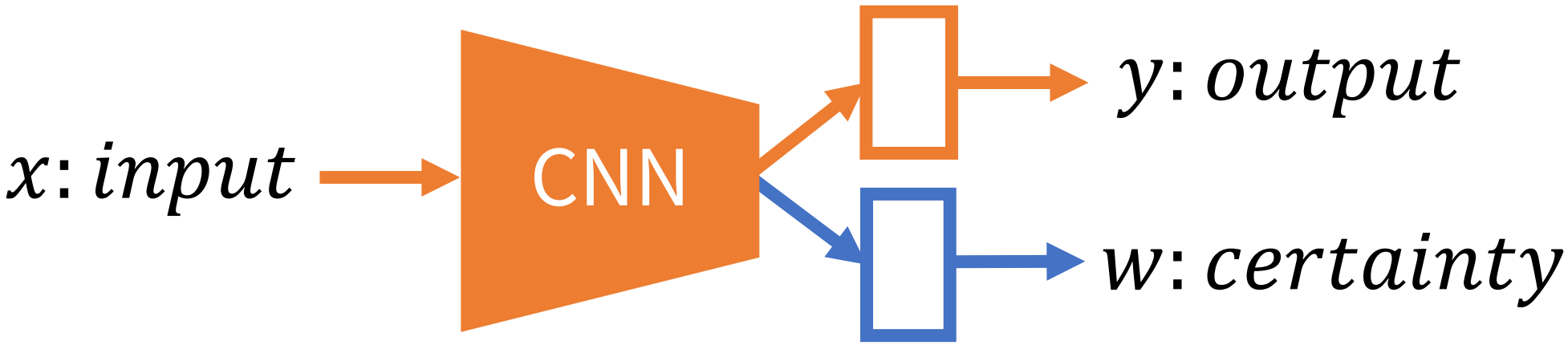
[2] Y. Gal. “Uncertainty in deep learning.”, *University of Cambridge*, 2016.
[3] A. Kendall, et al. “What uncertainties do we need in bayesian deep learning for computer vision?”, *NIPS*, 2017.

Existing Works for Aleatoric Uncertainty Estimation

$$L = \frac{1}{b}||y - y^*|| - log\frac{1}{b}$$

$$w = log\frac{1}{b}, r = ||y - y^*||$$

$$L = e^w r - w$$



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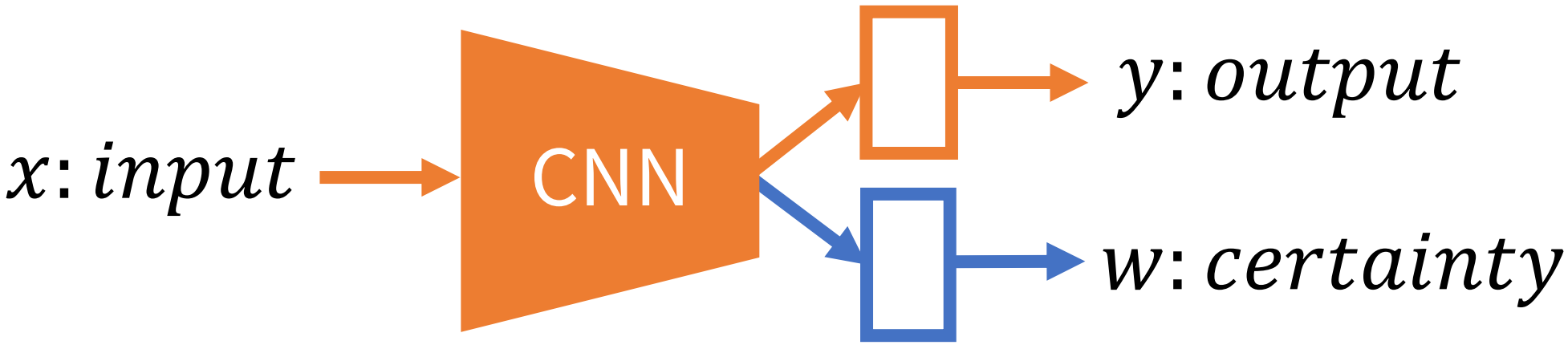
$$L = \frac{1}{b}||y - y^*|| - log\frac{1}{b}$$

$$w = log\frac{1}{b}, r = ||y - y^*||$$

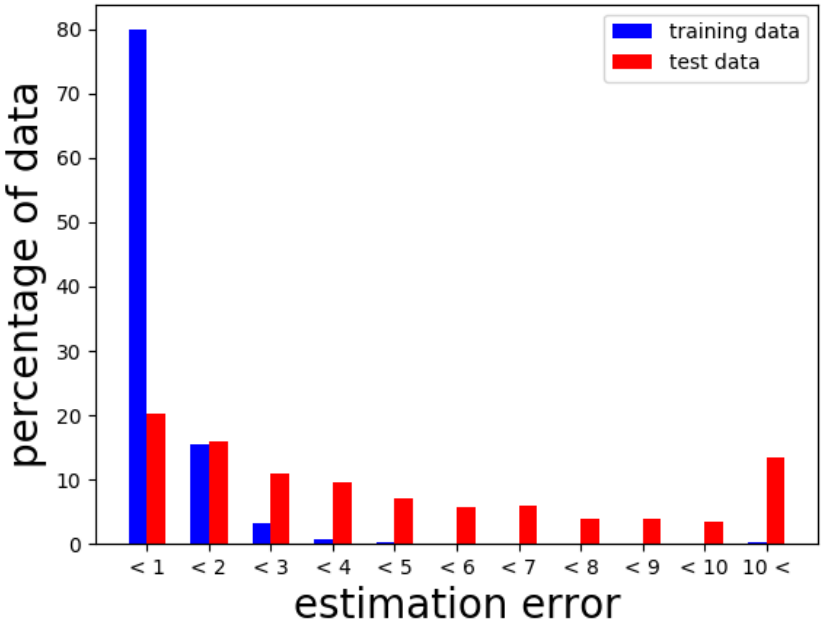
$$L = e^w r - w$$

- inseparability of r and w
- w is optimized by training error r



A Problem of the Existing Works

There is a large difference between training errors and test errors.
→ Optimizing w with training errors results in an inappropriate error estimation.

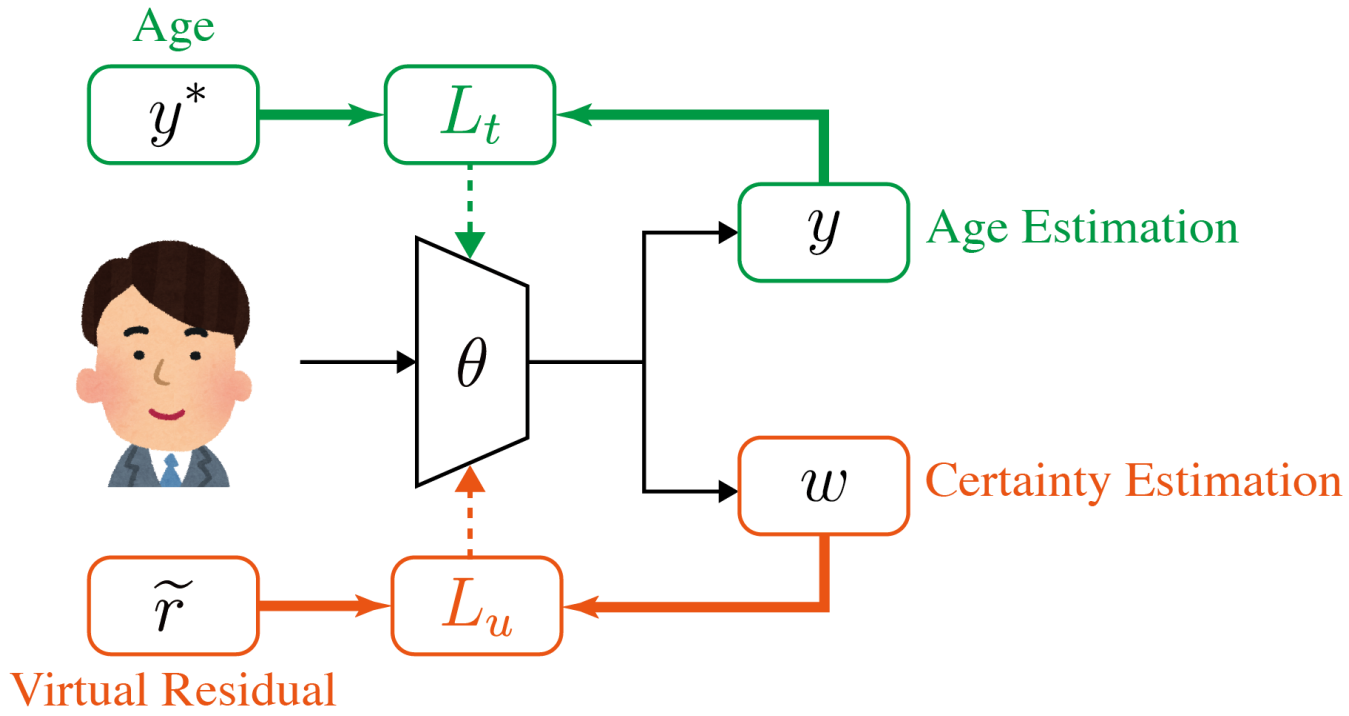


The distribution of errors during an age estimation task.

Our Proposed Method

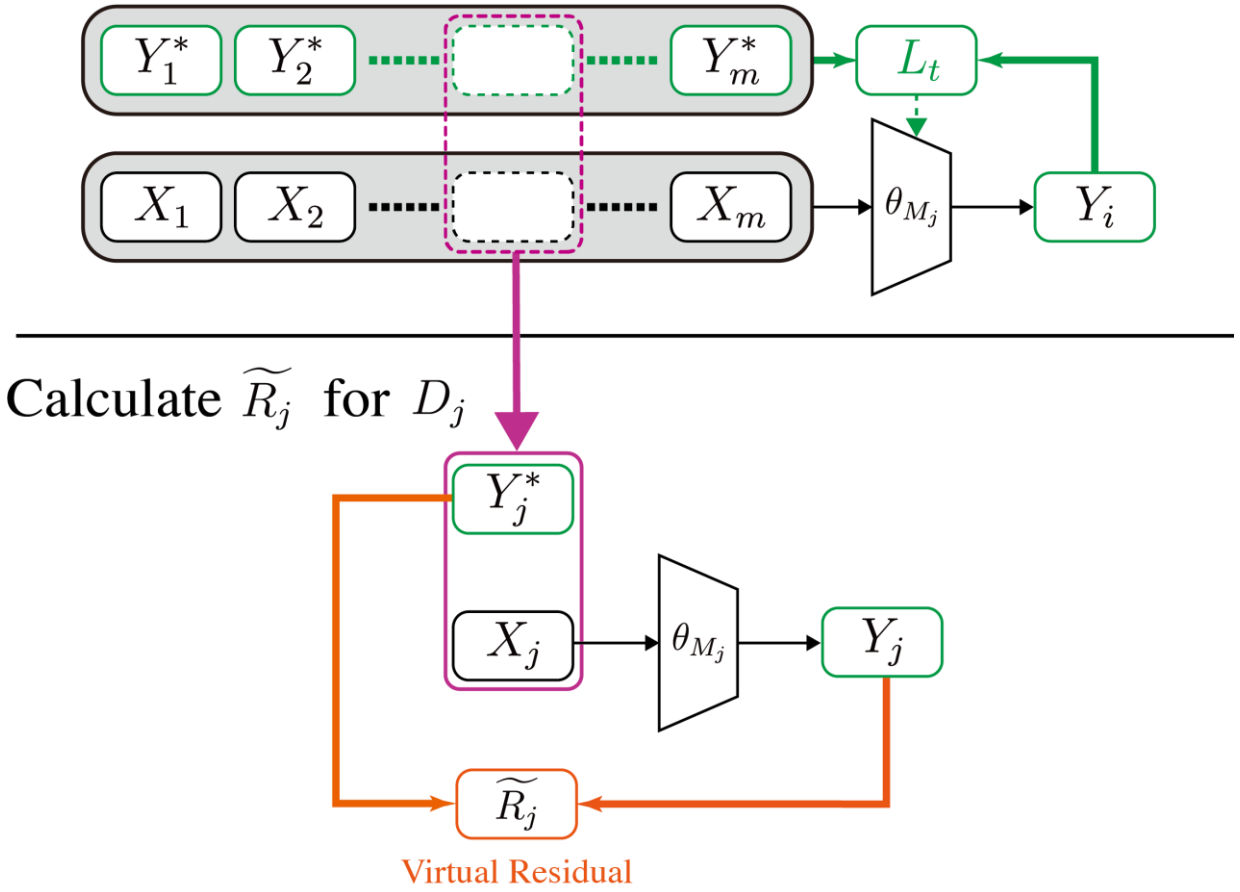
- Separate the loss function
- Use virtual residuals $\tilde{r}$

$$L = r + \lambda(e^{w}\tilde{r} - w)$$



Production of Virtual Residuals

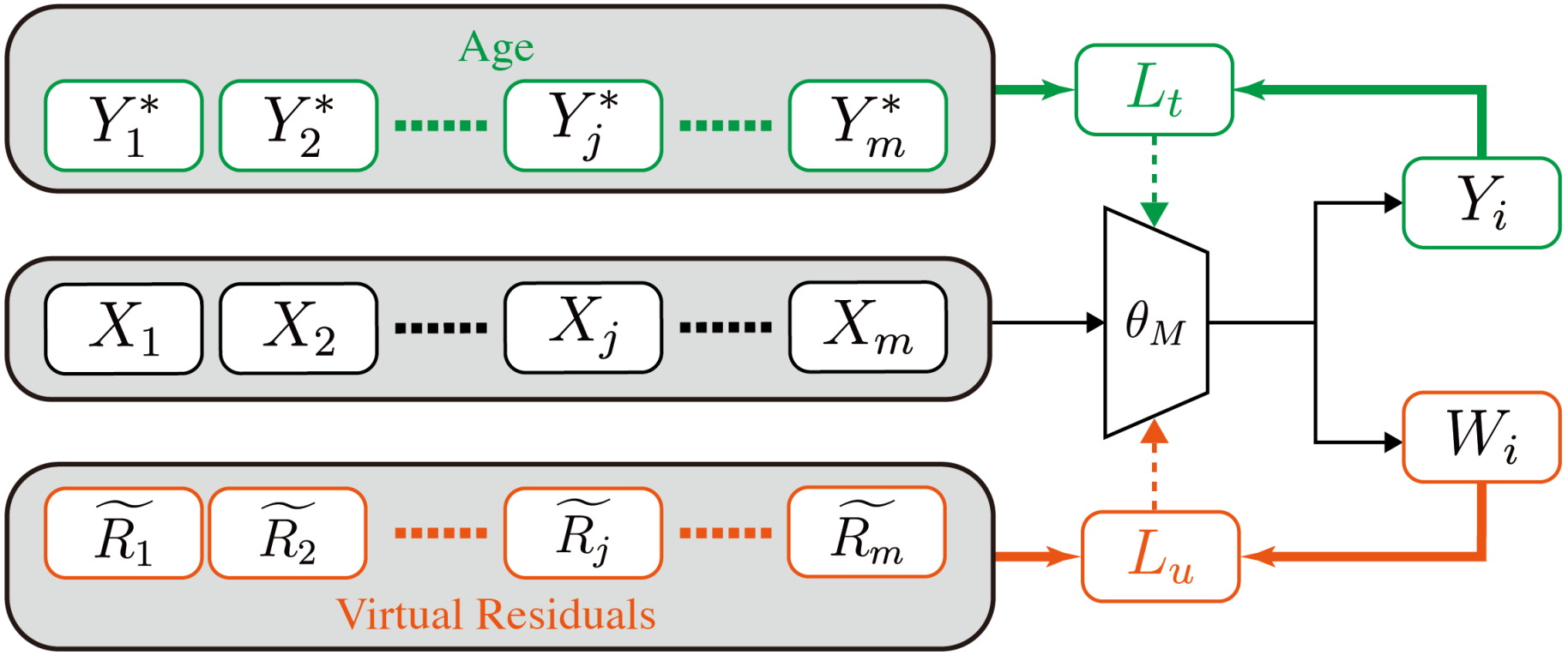
- Divide the training dataset and remove one subset
- Save validation errors of the removed subset



Optimization using Virtual Residuals

- Use saved validation errors as virtual residuals
- w is optimized by the virtual residuals

$$L = r + \lambda(e^{w}\tilde{r} - w)$$



The Existing Method [Kendall+, 2017]

$$L = e^{w} r - w$$

- r and w are inseparable
- cannot adjust the balance

- use training error r during w optimization

Proposed Method

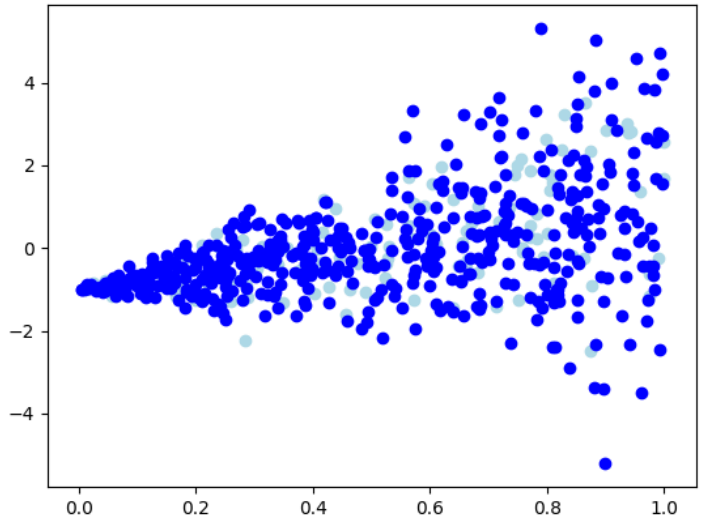
$$L = r + \lambda(e^{w}\tilde{r} - w)$$

- r and w are separable
- can adjust the balance with

- use validation error during w optimization

Experiments

1. Simulation



2. Age Estimation

UTKFace[4]

3. Depth Estimation

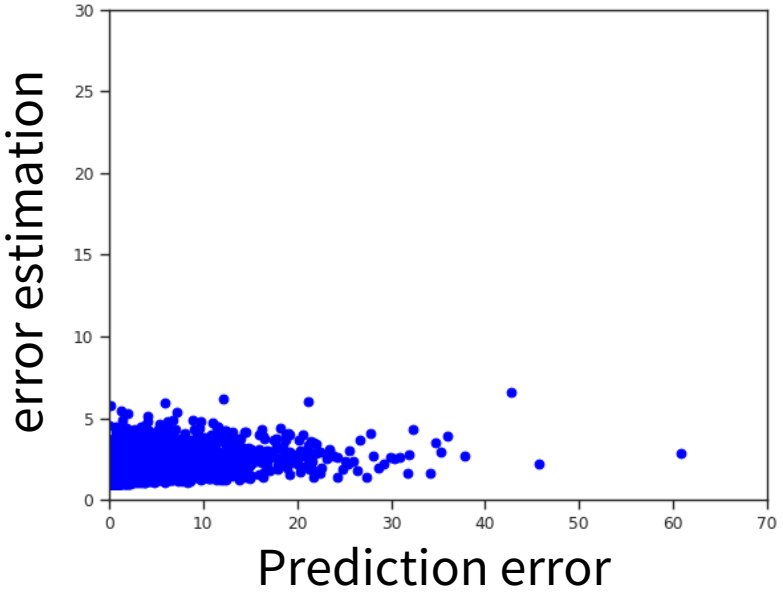
NYU depth v2[1]

[1] N. Silberman, et al. “Indoor segmentation and support inference from rgbd images.”, *ECCV*, 2012.
[4] Z. Zhang, et al. “Age Progression/Regression by Conditional Adversarial Autoencoder”, CVPR, 2017.

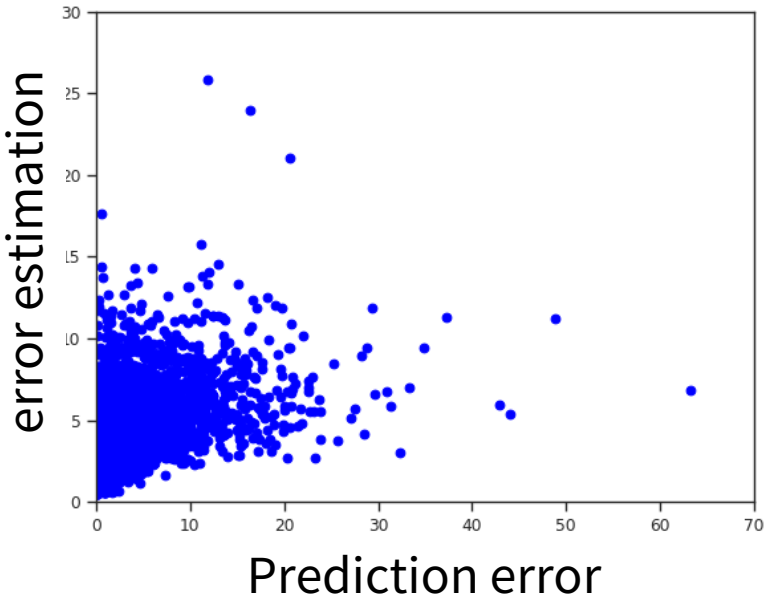
Experimental Result

- The existing method estimates errors to be much smaller
- Out method is effective in prediction of errors of the regression

Error estimations during the age estimation task.



[Kendall+, 2017]



Our method

Experimental Result

- Our method outperformed the existing one in the quantitative evaluation

Quantitative evaluations during the age estimation task.

Method	Target metric	Uncertainty metrics	
	Target RMSE (↓)	eRMSE (↓)	PiR (0.5) (↑)
L1	7.37	-	-
[Kendall+, 2017]	7.51	6.10	0.352
Our method	7.27	4.99	0.523

Conclusion

- Problem
  - Aleatoric uncertainty estimation during regression tasks
  - The existing method tends to underestimate uncertainties

- Our Proposed Method
  - Introduced a separate formulation
  - Trained the model using virtual residuals
  - Effectively estimate test errors

- Experimental Results
  - Outperformed the existing method in three different tasks