

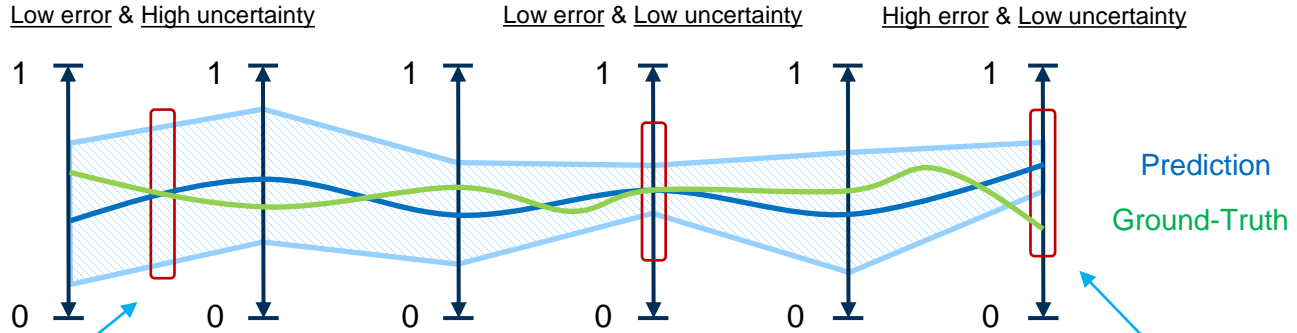
Variational Imbalanced Regression: Fair Uncertainty Quantification via Probabilistic Smoothing

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Motivation

Uncertainty Quantification



Underconfident

Overconfident

Age Distribution



Method (Feature Space): Constructing $q(z_i|\{x_i\}_{i=1}^N)$

I.I.D. vs. *N.I.D.* (Neighboring and Identically Distributed)

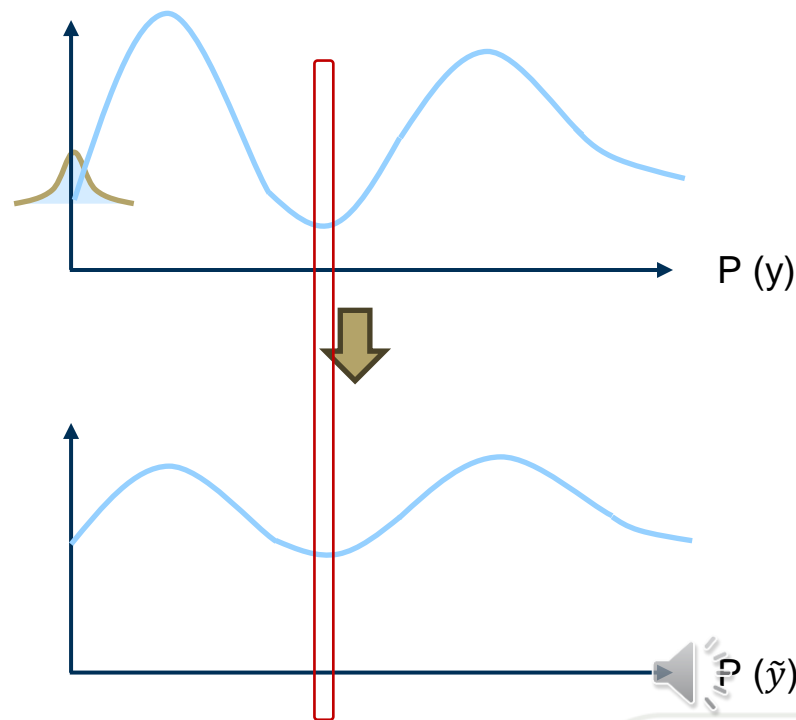
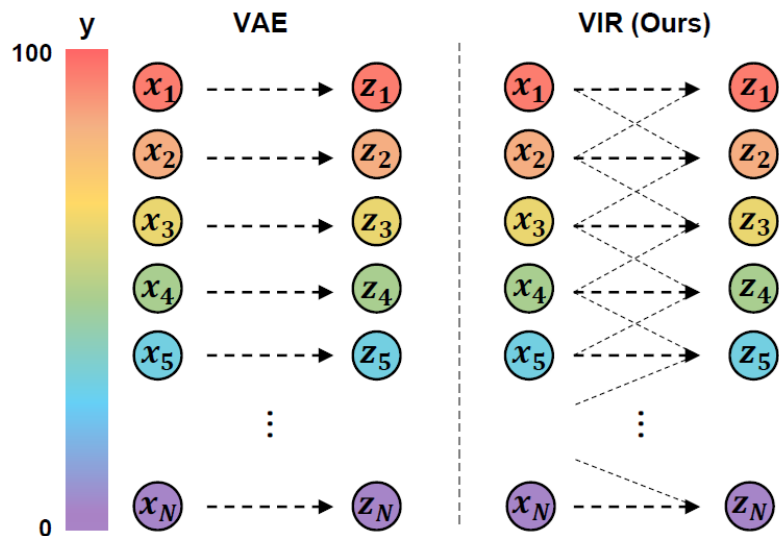
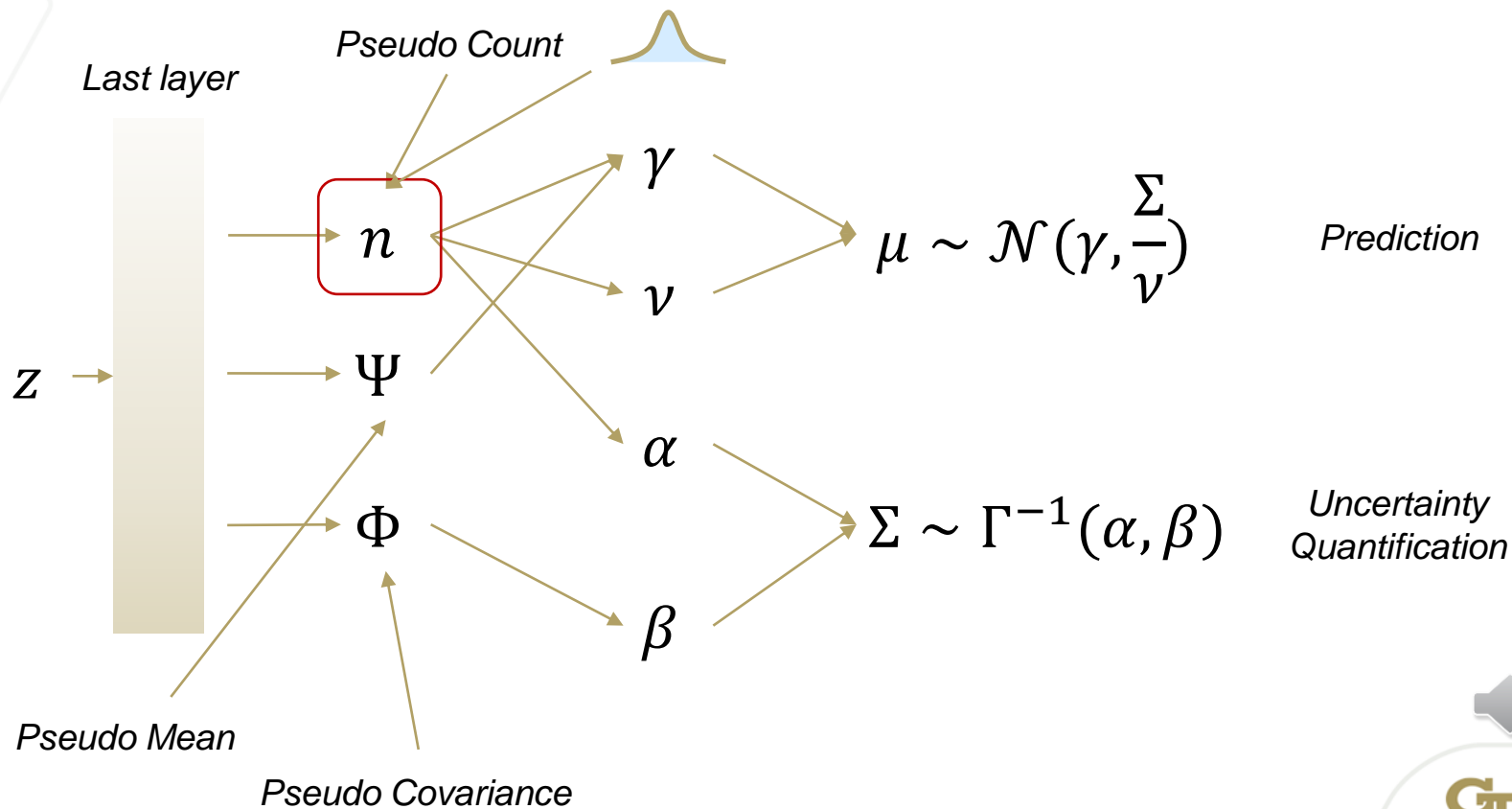


Figure 1: Comparing inference networks of typical VAE [25] and our VIR. In VAE (left), a data point's latent representation (i.e., z) is affected only by itself, while in VIR (right), neighbors participate to modulate the final representation.

Method (Label Space): Constructing $p(y_i|z_i)$



Theorem: Generalization Bound

Theorem 4.1 (Generalization Bound of VIR). *In imbalanced regression with bins \mathcal{B} , for any finite hypothesis space of predictions $\mathcal{H} = \{\hat{Y}_1, \dots, \hat{Y}_{\mathcal{H}}\}$, the transductive prediction error of the empirical risk minimizer \hat{Y}^{ERM} using the **VIR estimator with estimated propensities \tilde{P} ($P_i > 0$)** and given training observations O from \mathcal{Y} with independent Bernoulli propensities P , is bounded by:*

$$R(\hat{Y}^{ERM}) \leq \underbrace{\hat{R}_{\text{VIR}}(\hat{Y}^{ERM} | \tilde{P}) + \frac{\Delta}{|\mathcal{B}|} \sum_{i=1}^{|\mathcal{B}|} \left| 1 - \frac{P_i}{\tilde{P}_i} \right|}_{\text{Bias Term}} + \underbrace{\frac{\Delta}{|\mathcal{B}|} \sqrt{\frac{\log(2|\mathcal{H}|/\eta)}{2}} \sqrt{\sum_{i=1}^{|\mathcal{B}|} \frac{1}{\tilde{P}_i^2}}}_{\text{Variance Term}}. \quad (7)$$

- Increase Bias;
- **Significantly** reduce Variance in the imbalanced setting;
- Lower Generalization Error.



Results

Metrics	MSE ↓				MAE ↓				GM ↓			
	All	Many	Medium	Few	All	Many	Medium	Few	All	Many	Medium	Few
VANILLA [49]	101.60	78.40	138.52	253.74	7.77	6.62	9.55	13.67	5.05	4.23	7.01	10.75
VAE [25]	99.85	78.86	130.59	223.09	7.63	6.58	9.21	13.45	4.86	4.11	6.61	10.24
DEEP ENSEMBLE [27]	100.94	79.3	129.95	249.18	7.73	6.62	9.37	13.90	4.87	4.37	6.50	11.35
INFER NOISE [29]	119.46	95								4.95	6.58	10.86
SMOTER [40]	114.34	95								4.65	5.69	8.49
SMOEN [5]	117.29	10								4.9	6.19	8.44
SQINV [49]	105.14	87								4.57	5.73	7.77
DER [1]	106.77	91								4.59	6.43	10.49
LDS [49]	102.22	85								4.39	5.8	7.45
FDS [49]	101.67	86								4.41	5.97	6.29
LDS + FDS [49]	99.46	84								4.36	5.45	6.79
RANKSIM [13]	83.51	71								4.13	5.37	6.89
LDS + FDS + DER [1]	112.62	94								4.75	6.74	7.68
VIR (OURS)	81.76±0.10	70.6								4.07±0.02	5.05±0.03	6.23±0.05
OURS vs. VANILLA	+19.84	+7.79	+47.05	+111.38	+0.78	+0.23	+2.08	+4.16	+0.64	+0.16	+1.96	+4.52
OURS vs. INFER NOISE	+37.70	+24.41	+58.37	+123.93	+1.54	+1.23	+2.26	+4.31	+1.16	+0.88	+1.53	+4.63
OURS vs. DER	+25.01	+20.68	+30.96	+67.33	+1.10	+0.92	+1.52	+3.15	+0.78	+0.52	+1.38	+4.26
OURS vs. LDS + FDS	+17.70	+13.49	+20.73	+66.91	+0.56	+0.62	+0.77	+1.28	+0.31	+0.29	+0.40	+0.56
OURS vs. RANKSIM	+1.75	+1.38	+7.67	+6.69	+0.03	+0.10	+0.37	+0.17	+0.12	+0.06	+0.32	+0.66



Conclusion

- ❑ **Identify the problem** of probabilistic deep imbalanced regression.
- ❑ **Propose VIR** to simultaneously cover two desiderata: balanced accuracy and uncertainty quantification.
- ❑ Show that VIR can achieve **better generalization bound**.

Code will be soon available at

<https://github.com/Wang-ML-Lab/variational-imbalanced-regression>.

Paper



Code

