Jerrick Gerald | Cover Letter

Oh, S. J., Murphy, K., Pan, J., Roth, J., Schroff, F., & Gallagher, A. (2019, August). *Modeling Uncertainty with Hedged Instance Embedding*. In Proceedings of arXiv:1810.00319v6 [cs.LG].

This paper explores how to handle uncertainty in machine learning models, focusing on instance embeddings used for tasks like image recognition and classification. The authors study how embeddings can reflect uncertainty when the input data is unclear, such as blurred or partially hidden images. The main research question they address is: *"How can we model uncertainty by hedging the location of each input in the embedding space?"* To answer this, they propose a method called **Hedged Instance Embedding (HIB)**, which treats embeddings as random variables rather than fixed points. This approach aims to improve model reliability by allowing embeddings to "hedge bets" when faced with uncertain inputs. One major challenge they identify is that traditional embeddings fail to capture uncertainty effectively, making them less reliable in real-world scenarios. The authors claim that their probabilistic approach can improve performance and reliability. They support this claim with evidence from experiments using a new dataset called **N-digit MNIST**, showing that HIB outperforms traditional methods, especially for ambiguous inputs. They also use **Monte Carlo sampling** and **contrastive loss** to measure the effectiveness of their method, evaluating it with **average precision (AP)** and **K-nearest neighbors (KNN)** tasks. In short, the paper suggests that incorporating uncertainty into embeddings can make AI models more robust and reliable, especially when dealing with unclear or ambiguous data.