Oversampling Highly Imbalanced Indoor Positioning Data using Deep Generative Models

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Abstract—The location fingerprinting method, which typically utilizes supervised learning, has been widely adopted as a viable solution for the indoor positioning problem. Many indoor positioning datasets are imbalanced. Models trained on imbalanced datasets may exhibit poor performance on the minority class(es). This problem, also known as the "curse of imbalanced data," becomes more evident when class distributions are highly imbalanced. Motivated by the recent advances in deep generative modeling, this paper proposes using Variational Autoencoders and Conditional Variational Autoencoders as oversampling tools to produce class-balanced fingerprints. Experimental results based on Bluetooth Low Energy fingerprints demonstrate that the proposed method outperforms SMOTE and ADASYN in both minority class precision and overall precision. To promote reproducibility and foster new research efforts, we made all the codes associated with this work publicly available.

Index Terms—ADASYN, Bluetooth Low Energy, Conditional Variational Autoencoders, Imbalanced Data, Indoor Positioning, Location Fingerprints, Oversampling, Recurrence Plots, SMOTE, Variational Autoencoders.

I. INTRODUCTION

Interest in indoor positioning research has substantially grown in recent years due to the multitude of applications enabled by indoor positioning, such as the Internet of Things (IoT) [1], Indoor Location-based Services [2], and Ambient Assisted Living [3]. Unlike outdoor positioning, where the Global Navigation Satellite System (GNSS) is the de facto standard for positioning, there is no universally agreed-upon solution for the indoor positioning problem. Among the techniques used for indoor positioning, location fingerprinting, or simply fingerprinting, has received the most attention because of its simplicity and ability to produce accurate positioning estimates [4]. The concept of fingerprinting is to identify indoor spatial locations based on location-dependent measurable features (i.e., location fingerprints) collected at predefined reference points (RPs). Examples of location fingerprints include radio frequency fingerprints (e.g., WiFi [5], Bluetooth [6], cellular [7]), magnetic field fingerprints [8], and hybrid fingerprints [9]. Fingerprinting typically utilizes supervised learning and is inherently dependent on labeled datasets. However, often real-world indoor positioning datasets are imbalanced, meaning that the class distribution of fingerprint samples is not uniform. For example, Table I illustrates discrepancies between the number of samples in the minority and majority classes of some publicly available indoor positioning datasets.

 TABLE I

 Examples of imbalanced indoor positioning datasets

Туре	Minority	Majority	Ratio
WiFi	1	2	1:2
BLE	36	78	$\approx 1:2$
BLE	240	1,680	$\approx 1:7$
Hybrid	18	208	$\approx 1:12$
BLE	2	34	1:17
Magnetic	17	404	$\approx 1:24$
WiFi	2	139	$\approx 1:70$
LoRaWAN	1	398	1:398
	Type WiFi BLE BLE Hybrid BLE Magnetic WiFi LoRaWAN	TypeMinorityWiFi1BLE36BLE240Hybrid18BLE2Magnetic17WiFi2LoRaWAN1	Type Minority Majority WiFi 1 2 BLE 36 78 BLE 240 1,680 Hybrid 18 208 BLE 2 34 Magnetic 17 404 WiFi 2 139 LoRaWAN 1 398

Training on imbalanced data may result in a model biased toward the majority class(es). The techniques used to address this problem can be grouped into four main approaches: data sampling [10], algorithmic modification [11], cost-sensitive learning [12], and ensemble learning [13]. This paper deals with data sampling and, in particular, with oversampling data techniques. To the best of our knowledge, no study exists that investigates the problem of imbalanced data in the context of indoor positioning. The main contribution of this paper is the application of a Variational Autoencoder (VAE) [14] and a conditional variant, referred to as a Conditional Variational Autoencoder (CVAE) [15], on a highly imbalanced indoor fingerprinting dataset. By using various performance evaluation metrics, the achieved results are compared to those obtained by two state-of-the-art oversampling methods known as Synthetic Minority Oversampling TEchnique (SMOTE) [10] and ADAptive SYNthetic (ADASYN) sampling [16]. The remainder of this paper is organized as follows: Section II describes the dataset used in this study, Section III outlines the experimental setup, and Section IV discusses the results and future research directions.

II. DATASET DESCRIPTION

Aranda *et al.* [19] introduced the dataset used in this study and made it publicly available. We chose this dataset because it is composed of Bluetooth Low Energy (BLE) fingerprints. BLE is a recently introduced low-power communication protocol. It was designed with the IoT in mind, so it has received widespread adoption in indoor positioning applications [25]. The data we used was collected from a three-story Physics Department building. Each floor was comprised



Fig. 1. A graphical representation of the collection environment showing 2D floor plans, RPs, and beacon locations

of two same-sized cubic structures joined by a hallway. Ten multi-slot BLE beacons were deployed per floor, and three different smartphones were used to collect fingerprints at various RPs. This paper is concerned with users' locations expressed symbolically instead of physically, also known as symbolic positioning [26]. Therefore, we treated each cubic structure on each side of a floor as an independent symbolic space. Since each symbolic space has different BLE signal propagation characteristics, it can be considered a unique class, and the symbolic positioning problem can be cast as a classification problem. We preprocessed the dataset to exclude any samples collected outside of the cubic structures and create an initially balanced dataset. Additionally, to account for differences in beacon transmission powers resulting from multi-slot configuration, we transformed all fingerprints into recurrence plots according to (1):

$$\begin{aligned} \boldsymbol{x} &= [x_1, x_2, \cdots, x_n]; R_{i,j} = |x_i - x_j|; \\ \boldsymbol{x} &\in \mathbb{R}^n : \{x_i, x_j \in \mathbb{R} \mid 0 \le x_i, x_j \le 1\} \end{aligned}$$
(1)

where x is a fingerprint vector of dimension n; x_i, x_j are standardized Received Signal Strength (RSS) measurements corresponding to beacons i and j, respectively; and $R_{i,j}$ represents the distance between two RSS measurements. After preprocessing, the balanced dataset contained a total of 8,500 samples per symbolic space. We allocated 80% of those for training and the remaining 20% for testing. Fig. 1 presents a 2D scheme depicting the collection environment, RPs, and beacon locations, while Fig. 2 displays the recurrence plot of a randomly selected fingerprint from each symbolic space.

III. EXPERIMENTAL SETUP

Q. Li *et al.* [27] demonstrated how site surveying costs can be reduced through the incorporation of Generative Adversarial Network (GAN)-synthesized fingerprints. In contrast,



Fig. 2. Examples of fingerprints transformed into recurrence plots

this paper addresses the problem of imbalanced fingerprint datasets using VAEs/CVAEs. In particular, our approach is inspired by applying deep generative models for data oversampling in domains such as fraud detection [28] and image processing [29]. We assessed the performance of VAEs and CVAEs by creating imbalanced versions of the training set. We applied these models to generate synthetic fingerprints of the minority symbolic space(s) so that all symbolic spaces are equally represented (i.e., an artificially balanced training set is created). Since we are interested in highly imbalanced data [30], we set the imbalance ratio to 1 : 100 using random downsampling. We used the artificially balanced training set to train a downstream classifier that acted as a positioning model that distinguished between different symbolic spaces. For this purpose, we chose a Support Vector Machine (SVM) since SVMs are extensively used in indoor positioning [31]. We used the scikit-learn implementation of SVM [32], with default parameters that were kept fixed for all experiments. We used the testing set, which is well-balanced and remains the same for all experiments, to quantify the performance of the classifier according to metrics Precision, Recall, and F1score as defined in [33]. The aim is to determine whether VAEs and CVAEs can learn the distribution of the minority symbolic space(s) to generate synthetic fingerprints that promote enhancements in the classifier's performance. The performance of the classifier trained on the imbalanced version of the training set serves as the baseline. Performance results are expressed as a relative change compared to the baseline as calculated by (2):

$$C_{\Phi} = \frac{\Psi_{\Phi} - \Psi_{\rm IMBALANCED}}{\Psi_{\rm IMBALANCED}}$$
(2)

where C_{Φ} is the relative change for a performance metric Ψ obtained using an oversampling technique Φ . Since there is a total of six symbolic spaces, we performed a total of five experiments. Each experiment corresponds to a different number of minority symbolic spaces ranging from 1 to 5. We conducted three trials for a given number of minority spaces (i.e., three imbalanced sets are constructed in which the spaces constituting a set are randomly chosen). For example, the experiment dealing with five minority spaces is composed of sets $\{0, 1, 2, 3, 5\}$, $\{0, 1, 3, 4, 5\}$, and $\{0, 1, 2, 3, 4\}$. The result is determined by averaging performance over all the trials. Table II presents the results of the experiments and compares them to those achieved by SMOTE and ADASYN as implemented in the imbalanced-learn library [34]. We

TABLE II			
DOWNSTREAM CLASSIFIER RESULTS (RELATI	VE TO	THE BASELIN	E)

		Minority			Majority			Overall		
Minority Classes	Method	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
1	SMOTE	-0.1597	11.0763	7.3103	0.048	-0.0153	0.0255	0.0049	0.0813	0.1511
	ADASYN	-0.1628	11.3157	7.419	0.0486	-0.0164	0.0254	0.0047	0.0822	0.1529
	VAE	-0.0572	9.6271	5.9637	0.0297	-0.0537	-0.0444	0.0117	0.0305	0.0592
	CVAE	-0.0775	2.6687	2.2359	0.0106	0.0001	0.0078	-0.0077	0.0234	0.0462
2	SMOTE	-0.1612	2.6073	1.7459	0.0552	-0.0731	0.0137	-0.0295	0.1778	0.2649
	ADASYN	-0.1619	2.6083	1.7461	0.0538	-0.0742	0.0129	-0.0306	0.1769	0.2643
	VAE	-0.0363	0.5386	0.5013	0.0128	-0.0001	0.0123	-0.0052	0.0504	0.0832
	CVAE	-0.0953	0.5552	0.4981	0.016	-0.0007	0.0141	-0.0268	0.0514	0.0843
3	SMOTE	-0.1863	3.9258	2.4359	0.234	-0.1229	0.101	-0.0323	0.3697	0.6369
	ADASYN	-0.1876	3.9276	2.4334	0.234	-0.0663	0.1318	-0.0332	0.3692	0.636
	VAE	-0.0453	1.533	1.2109	0.0703	-0.0039	0.0508	-0.0029	0.1637	0.305
	CVAE	-0.077	1.3086	1.0386	0.0672	-0.0029	0.0473	-0.0242	0.1401	0.2644
4	SMOTE	-0.0907	2.1388	1.5017	0.5263	-0.1097	0.2738	0.024	0.5032	0.8718
	ADASYN	-0.0932	2.1385	1.4979	0.5242	-0.1139	0.2703	0.0216	0.5001	0.8682
	VAE	0.0282	0.9697	0.8676	0.1912	-0.0064	0.1279	0.0584	0.2597	0.4881
	CVAE	0.0618	0.7553	0.6843	0.1363	-0.0045	0.0927	0.0756	0.2027	0.3808
5	SMOTE	0.012	0.2202	0.2808	0.1315	0.0601	0.3246	0.0283	0.1845	0.2881
	ADASYN	0.0084	0.2119	0.2724	0.1245	0.0638	0.3231	0.0242	0.1789	0.2809
	VAE	0.0705	0.1046	0.1461	0.0419	0.0477	0.1499	0.0666	0.0919	0.1468
	CVAE	0.0782	0.1008	0.1433	0.0555	0.0423	0.1457	0.0751	0.0877	0.1438

used the default parameters for SMOTE and ADASYN and we kept them fixed for all the experiments. Similarly, VAE and CVAE architecture and hyperparameters implemented using Keras [35] were kept fixed for all the experiments. The model specifications for VAE and CVAE are provided in Table III and a general scheme of the experimental setup is presented in Fig. 3.

IV. DISCUSSION AND CONCLUSION

The results in Table II show that, in all the experiments, using synthetic fingerprints generated by VAE, CVAE, SMOTE, and ADASYN all lead to an improved F1-score for the minority symbolic space(s) compared with classifiers trained on imbalanced datasets. Moreover, in all the experiments, every oversampling technique also resulted in a better F1-score for the majority symbolic space(s) and all spaces overall. This suggests that these oversampling techniques can enhance a classifier's overall learning ability, given that improvements are not isolated to the performance on the minority space(s). Finally, in general, SMOTE and ADASYN outperform VAE and CVAE. However, unlike VAE and CVAE, SMOTE and ADASYN are algorithms specifically designed to handle imbalanced data. Additionally, we expect that by fine-tuning VAE and CVAE architecture and hyperparameters, we can achieve comparable results to, if not better than, those obtained by SMOTE and ADASYN. Confirming this conjecture is a topic for future research. Furthermore, as part of future research, we intend to undertake a more in-depth analysis of the results to answer questions such as "Why does VAE generally produce better overall F1-scores than CVAE?" and "Why does VAE yield better minority space Precision and overall Precision when the minority spaces represent 50% or less of the overall spaces, while CVAE performs better on these metrics when the minority spaces represent over 50% of the overall spaces?". In addition, we would like to apply VAE and CVAE to other fingerprint types and investigate the effectiveness of other deep generative models such as GANs and Conditional GANs (CGANs) for oversampling fingerprint data. Computing scripts associated with this work are publicly available in our GitHub repository [36].



Fig. 3. Scheme of the experimental setup

TABLE III VAE/CVAE SPECIFICATIONS. THE CODE FOR VAE AND CVAE IS INSPIRED BY [37] AND [38], RESPECTIVELY, AND EXECUTED ON GOOGLE COLAB IN A GRAPHICS PROCESSING UNIT (GPU) RUNTIME.

Order	Layer type	Output size	Filters	Kernel size	Strides	Activation		
VAE (encoder)								
1	Input (recurrence plot)	(30,30)	-	-	-	-		
2	Convolution	(15,15)	8	(4,4)	(2,2)	ReLu		
3	Convolution	(8,8)	16	(4,4)	(2,2)	ReLu		
4	Convolution	(8,8)	16	(4,4)	(2,2)	ReLu		
5	Flatten	-	-	-	-	-		
6	Dense	8	-	-	-	ReLu		
7(a)	Dense (µ)	2	-	-	-	Linear		
7(b)	Dense (σ)	2	-	-	-	Linear		
		VAE (decod	er)					
1	Input (sample from distribution)	2	-	-	-	-		
2	Dense	1,024	-	-	-	ReLu		
3	Reshape	(8,8,16)	-	-	-	-		
4	Deconvolution	(15,15)	16	(4,4)	(2,2)	ReLu		
5	Deconvolution	(30,30)	8	(4,4)	(2,2)	ReLu		
6	Deconvolution (recurrence plot)	(30,30)	1	(3.3)	(1,1)	Sigmoid		
optimize	er: Adam $(lr = 1e-4)$: batch size: 23: o	biective function	n: binary o	cross-entropy +	Kullback-	Leibler divergence		
		CVAE (man	1)	F7 -				
1()	Innut (management and allot)	CVAE (encod						
1(a)	Input (recurrence pior)	(30,30)		-	-	-		
1(0)	Dense	000		-	-	T in sur		
2	Delise	900		-	-	Linear		
3	Constants (maximum a plat & label)	(30, 30, 1)		-	-	-		
4	Concatenate (recurrence piot & label)	(30,30,2)	10	-	-	- D-L-		
0	Convolution	(13,13)	10	(4,4)	(2,2)	ReLU		
0 7	Convolution	(8,8)	32	(4,4)	(2,2)	ReLu		
6	Flatten	-	-	-	-	-		
8	Dense	10	-	-	-	KeLu		
9(a)	Dense (μ)	2	-	-	-	Linear		
9(b)	Dense (σ)	2	-	-	-	Linear		
		CVAE (decor	ter)	1				
1(a)	Input (sample from distribution)	2	-	-	-	-		
1(b)	Input (label)	6	-	-	-	-		
2	Concatenate (sample & label)	8	-	-	-			
3	Dense	2,048	-	-	-	ReLu		
4	Reshape	(8,8,32)		-	-	11.		
5	Deconvolution	(15,15)	32	(4,4)	(2,2)	ReLu		
6	Deconvolution	(30,30)	16	(4,4)	(2,2)	ReLu		
7	Deconvolution (recurrence plot)	(30,30)	1	(4,4)	(1,1)	Sigmoid		
optimizer: Adam $(lr = 1e-4)$: batch size: 64: objective function: binary cross-entropy + Kullback-Leibler divergence								

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