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# Preserving Geo-Indistinguishability of the Emergency Scene to Predict Ambulance Response Time

Héber H. Arcolezzi <sup>1\*</sup> , Selene Cerna <sup>1</sup> , Christophe Guyeux <sup>1\*</sup> , and Jean-François Couchot <sup>1</sup> 

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**Abstract:** Emergency medical services (EMS) provide crucial emergency assistance and ambulatory services. One key measurement of EMS's quality of service is their ambulances' response time (ART), which generally refers to the period between EMS notification and the moment an ambulance arrives on the scene. Due to many victims require care within adequate time (*e.g.*, cardiac arrest), improving ARTs is vital. This paper proposes to predict ARTs using machine learning (ML) techniques, which could be used as a decision-support system by EMS to allow a dynamic selection of ambulance dispatch centers. However, one well-known predictor of ART is the location of the emergency (*e.g.*, if it is urban or rural areas), which is *sensitive data* because it can reveal who received care and for which reason. Thus, we considered the 'input perturbation' setting in the privacy-preserving ML literature, which allows EMS to sanitize each location data independently and, hence, ML models are trained only with sanitized data. In this paper, geo-indistinguishability was applied to sanitize each emergency location data, which is a state-of-the-art formal notion based on differential privacy. To validate our proposals, we used retrospective data of an EMS in France, namely, Departmental Fire and Rescue Service of Doubs, and publicly available data (*e.g.*, weather and traffic data). As shown in the results, the sanitization of location data and the perturbation of its associated features (*e.g.*, city, distance) had no considerable impact on predicting ARTs. With these findings, EMSs may prefer using and/or sharing sanitized datasets to avoid possible data leakages, membership inference attacks, or data reconstructions, for example.

**Keywords:** Emergency medical services; Emergency medicine; Decision support system; Pre-hospital emergency care; Ambulance response time; Machine learning; Geo-indistinguishability; Differential privacy; Privacy-preserving machine learning; Input perturbation.

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## 1. Introduction

Ambulance response time (ART) is a key component for evaluating pre-hospital emergency medical services (EMS) operations. ART refers to the period between the notification and the moment an ambulance arrives at the emergency scene [1,2], and it is normally divided into two periods: the pre-travel delay, from the notification to the ambulance dispatch, and the travel time, from the ambulance dispatch to arrival on-scene. In many urgent situations (*e.g.*, cardiovascular emergencies, trauma, or respiratory distress), the victims need first-aid treatment within adequate time to increase survival rate [1–6] and, hence, improving ART is vital.

In many parts of the world, such as France, fire departments are responsible for many critical situations, including fires, hazards, severe storms, floodings, as well as non-urgent and urgent EMS calls (*e.g.*, traffic accidents, drowning). In this paper, we analyzed EMS operations of the Departmental Fire and Rescue Service of Doubs (SDIS 25), which has 71 centers currently deployed across the Doubs region in France to attend to its population. As noticed in [7,8], the SDIS 25 and fire departments in general, have been facing a continuous increase in the number of interventions over the years, which

38 may have adverse consequences on ARTs. For instance, the pre-travel delay affects  
39 directly ARTs if there is a lack of human and material resources when a call is received.  
40 This means, if there is a lack of firefighters, ambulances, or both, ART may be higher  
41 than allowed and, hence, a breakdown in the SDIS 25 service occurs [9]. This inability to  
42 assist within the time limits impacts negatively both EMS and victims because the safety  
43 of a certain area or population will be at risk. Thus, there is a need for an intelligent ART  
44 prediction system, which can assist SDIS 25 (and EMS, in general) in the dispatching of  
45 ambulances.

46 Indeed, predicting ART is useful for many reasons. First of all, it can help in  
47 choosing the best center to provide the ambulance. At present, for SDIS 25, each city  
48 in the department is associated with an ordered list of centers with the needed engine  
49 to respond, so that the first centers are the most likely to provide a rapid and adequate  
50 response. This sorting is guided both by the travel time needed to get from the center to  
51 the city and by the material and human resources of the center. However, this ordering  
52 of centers by city is fixed once and for all. While it does take into account the actual  
53 distance of the travel (not the Euclidean distance, for example), it does not consider  
54 the state of the road traffic, weather conditions, etc. This way, a center might be a little  
55 closer to the emergency scene than another, but may occasionally have a longer travel  
56 time due to traffic congestion. Predicting ART would therefore make it possible to move  
57 from static center scheduling to dynamic scheduling. It would also make it possible  
58 to estimate the exit time of vehicles partially and to see in advance whether, at a given  
59 moment, a center is at risk of running out of ambulances. In other words, it enables  
60 the anticipation of breakdowns and the redeployment of resources. Lastly, in the long  
61 term, it can be an element of a simulator to determine the evolution of response time and  
62 breakdowns during the creation or relocation of a center, the modification of resources  
63 by the center, etc.

64 As aforementioned, an important factor of ART is the *location* of the intervention,  
65 *e.g.*, in dense urban areas, the distance may be short, but the travel time may be longer  
66 due to traffic congestion. On the other hand, travel distance and travel time may be  
67 longer for rural areas. In other words, the location information is of great importance  
68 for the prediction of travel time and, naturally, ART [10,11]. However, the location of an  
69 emergency is also regarded as *sensitive data* because it can reveal who received care and  
70 for which reason. For example, by knowing that one intervention took place in front of  
71 the house of a debilitated person, attackers with auxiliary information may accurately  
72 infer that this person received care and (mis)use this information for their own good.  
73 Indeed, location privacy is an emerging and active research topic in the literature [12–14]  
74 as publicly exposing users' location raises major privacy issues. A common way to  
75 achieve location privacy is by applying a *location obfuscation* mechanism. In [14], the  
76 authors proposed geo-indistinguishability (GI), which is based on the state-of-the-art  
77 differential privacy (DP) [15] model, to protect the location privacy of users. GI has  
78 received considerable attention due to its effectiveness and simplicity of implementation  
79 (*e.g.*, Location Guard [16]).

80 In this paper, we propose to sanitize, independently, each emergency location data  
81 with GI before training any ML techniques to predict ARTs. In our context, besides the  
82 own location, with the exact coordinates of both SDIS 25 centers and the emergency  
83 scenes, one can retrieve important features such as the distance and estimated travel  
84 time. However, if the location is sanitized via GI, many other explanatory variables  
85 (*e.g.*, distance, travel time, city) would be 'perturbed' too. In the privacy-preserving data  
86 mining literature, training ML models with sanitized data is common practice [7,17–  
87 22], which is also known as *input perturbation* [23]. Different from objective [24] and  
88 gradient [25] perturbation settings, input perturbation is the easiest method to apply and  
89 it is independent of any ML and post-processing techniques. We also remark that input  
90 perturbation is in accordance with real-world applications where EMS would only use

91 and/or share sanitized data with trusted third parties to *train* and develop ML-based  
92 decision support systems.

93 To summarize, this paper proposes the following contributions:

- 94 • Recognize the most influential variables when building accurately ML-based mod-  
95 els to predict ART. This would allow other EMS to collect these variables and  
96 recreate our methodology or develop their own considering their policies.
- 97 • Evaluate the effectiveness of several values of  $\epsilon$  (*i.e.*, the privacy budget), to sani-  
98 tize emergency location data with GI and train ML-based models to predict ART.  
99 To the author's knowledge, this is the first work to assess the impact of geo-  
100 indistinguishability on sanitizing the location of emergency scenes when training  
101 ML models for such an important task. While predicting ART is a means to allow  
102 EMS to save more lives, we notice that it is also possible to do so while preserving  
103 the victims' privacy.

104 **Outline:** The remainder of this paper is organized as follows. In Section 2, we describe  
105 the material and methods used in this work, *i.e.*, the geo-indistinguishability privacy  
106 notion that we are considering, the data presentation (context, collection, and analysis),  
107 the sanitization of emergency scenes with GI, the ML models, and the experimental  
108 setup. In Section 3, we present the results of our experiments and our discussion. Lastly,  
109 in Section 4, we present the concluding remarks and future directions.

## 110 2. Materials and Methods

111 In this section, we revise the notion of privacy considered in this paper, namely,  
112 geo-indistinguishability (Subsection 2.1), we provide a description of the processing of  
113 interventions by SDIS 25 (Subsection 2.2), the data collection process (Subsection 2.3),  
114 the analysis of SDIS 25 ARTs (Subsection 2.4), the GI-based sanitization of emergency  
115 location data (Subsection 2.5), the ML models used for predicting ARTs (Subsection 2.6),  
116 and the experimental setup (Subsection 2.7).

### 117 2.1. Geo-indistinguishability

118 Differential privacy [15] has been accepted as the *de facto* standard for data privacy.  
119 DP was developed in the area of statistical databases but it is now applied to several  
120 fields. Furthermore, DP has also been extended to a local model (*a.k.a.* LDP [23]) in  
121 which users sanitize their data before sending it to the server. While DP is well-suited to  
122 the case of trusted curators, with LDP, users do not need to trust the curator.

123 Geo-indistinguishability [14] is based on a generalization of DP developed in [26]  
124 and has been proposed for preserving location privacy without the need of a trusted  
125 curator (*e.g.*, a malicious location-based service – LBSs). A mechanism satisfies  $\epsilon$ -GI  
126 if for any two locations  $x_1$  and  $x_2$  within a radius  $r$ , the output  $y$  of them is  $(\epsilon, r)$ -geo-  
127 indistinguishable if we have:

$$\frac{\Pr(y|x_1)}{\Pr(y|x_2)} \leq e^{\epsilon r}, \forall r > 0, \forall y, \forall x_1, x_2 : d(x_1, x_2) \leq r.$$

128 Intuitively, this means that for any point  $x_2$  within a radius  $r$  from  $x_1$ , GI forces the  
129 corresponding distributions to be at most  $l = \epsilon r$  distant. In other words, the level of  
130 distinguishability  $l$  increases with  $r$ , *e.g.*, an attacker can distinguish that the user is in  
131 Paris rather than London but can hardly (controlled by  $\epsilon$ ) determine the user's exact  
132 location. Although both GI and DP use the notation of  $\epsilon$  to refer to the privacy budget,  
133 they cannot be compared directly because  $\epsilon$  in GI contains the unit of measurement (*e.g.*,  
134 meters).

135 On the continuous plane (as we consider in this paper), an intuitive polar Laplace  
136 mechanism has been proposed in [14] to achieve GI, which is briefly described in the  
137 following. Rather than reporting the user's true location  $x \in \mathbb{R}^2$ , we report a point  
138  $y \in \mathbb{R}^2$  generated randomly according to  $D_\epsilon(y) = \frac{\epsilon^2}{2\pi} e^{-\epsilon d_2(x,y)}$ . Algorithm 1 shows the

139 pseudocode of the polar Laplace mechanism in the continuous plane. More specifically,  
 140 the noise is drawn by first transforming the true location  $x$  to polar coordinates. Then,  
 141 the angle  $\theta$  is drawn randomly between  $[0, 2\pi)$  (line 3), and the distance  $r$  is drawn from  
 142  $C_e^{-1}(p)$  (line 5), which is calculated using the negative branch  $W_{-1}$  of the Lambert  $W$   
 143 function. Finally, the generated distance and angle are added to the original location.

---

**Algorithm 1** Polar Laplace mechanism in continuous plane [14]

---

1: **Input** :  $\epsilon > 0$ , real location  $x \in \mathbb{R}^2$ .  
 2: **Output** : sanitized location  $y \in \mathbb{R}^2$ .  
 3: Draw  $\theta$  uniformly in  $[0, 2\pi)$   
 4: Draw  $p$  uniformly in  $[0, 1)$   
 5: Set  $r = C_e^{-1}(p) = -\frac{1}{\epsilon} \left( W_{-1} \left( \frac{p-1}{e} \right) + 1 \right)$   
 6: **return** :  $y = x + \langle r \cos(\theta), r \sin(\theta) \rangle$

---

144 *2.2. Process Flow description*

145 The Departmental Fire and Rescue Service of Doubs currently has 71 centers de-  
 146 ployed throughout the region of Doubs, France, serving a population of around 540,000  
 147 people. The focus of this paper is on interventions with *victims* that were further trans-  
 148 ported to hospitals. In these interventions, there was a need for an *emergency and victim*  
 149 *assistance vehicle* (a.k.a. Véhicule de Secours et d'Assistance aux Victimes - VSAV). VSAVs  
 150 are equipped with adequate material and personnel for first-aid treatment in urgent  
 151 situations. In this paper, we interchangeably use the term 'ambulance' when referring to  
 152 VSAV.

153 The process of an intervention is briefly described in the following. First, an  
 154 emergency call is received and treated by an operator. Next, the adequate crew/engine  
 155 is notified ( $t_1$ ). Once the sufficient armament is gathered, the ambulance goes to the  
 156 emergency scene ( $t_2$ ). Upon arriving on-scene, the crew uses a mechanical system to  
 157 report their arrival ( $t_3$ ). We focus on the ART period, which is calculated as:  $ART =$   
 158  $t_3 - t_1$ .

159 The operation process to decide the adequate SDIS 25 center to attend the interven-  
 160 tion depends on the exact *location* of the intervention. As stated previously, there is a city,  
 161 a district, and a zone that jointly define a list of priority centers, which are responsible  
 162 for the call. The reason for such a list is because a single center may not have sufficient  
 163 resources at time  $t_1$  to attend an intervention. In this case, if the first center of the list  
 164 does not have sufficient resources, another center(s) would be in charge of the call. Also,  
 165 many situations may generate several victims (e.g., traffic accidents, floods). In these  
 166 cases, a single intervention can require more than one ambulance, which can come from  
 167 different centers depending on the availability of resources. This means different ARTs  
 168 for the same intervention and, therefore, we focus on each ambulance in our analysis  
 169 and predictions.

170 In addition, although in some countries the *reason* of the emergency may require  
 171 a recommended ART [27,28], for SDIS 25, ART depends on the *Zone* as detailed in [9].  
 172 There are three zones: Z1 refers to urban areas, Z2 refers to semi-urban areas, and  
 173 Z3 refers to rural ones. Therefore, SDIS 25 ambulances should arrive on-scene with  
 174  $ART \leq 10$  minutes (min) on Z1 and with  $ART \leq 25$  min on Z2 and Z3, i.e., including  
 175 the pre-travel delay (gathering armament) and travel-time. If these time limits are not  
 176 reached, a breakdown in SDIS 25 services is generated [9] and the victim state may be  
 177 negatively impacted [1,5]. Lastly, SDIS 25 may also help other EMS outside the Doubs  
 178 region, and in this case, there is no pre-defined ART limit by SDIS 25.

179 *2.3. Data collection*

180 We used retrospective data of EMS operations recorded by SDIS 25. All interven-  
 181 tions with *victim*, that were attended by SDIS 25 centers with a VSAV, were eligible

182 for inclusion. These data covered the period of January 2006 to June 2020. The main  
 183 attributes of these data are described in the following:

- 184 • *ID* is a unique identifier for each intervention;
- 185 • *SDate* is the time SDIS 25 took charge of the intervention by processing the call;
- 186 • *ADate* is the time when an ambulance arrived on the emergency scene;
- 187 • *Center* is the SDIS 25 center from which the ambulance left;
- 188 • *Location* is the precise location (latitude, longitude) of the intervention;
- 189 • *Zone* is either urban (Z1), semi-urban (Z2), or rural (Z3);
- 190 • *City* is the municipality where the intervention took place. A city may have zero or  
 191 more *Districts*.

192 Each ambulance represents one sample, *i.e.*, a single intervention may have received  
 193 one or more ambulances. The ART variable was calculated as  $ART = ADate - SDate$ .  
 194 We excluded outlying observations with ART of less than 1 minute and with ART of more  
 195 than 45 minutes, which represented less than 1.4% of the original number of samples.

196 Using *SDate*, we have added temporal information such as: year, month, day,  
 197 weekday, hour, and categorical indicators to denote holidays, end/start of the month,  
 198 and end/start of the year. Besides, with the exact coordinates from both *Center* and  
 199 emergency's *Location*, we calculated the great-circle distance<sup>1</sup> to add as a feature, which  
 200 is the shortest distance between two points on the surface of a sphere. We have added  
 201 the number of interventions in the past hour and the number of active interventions in  
 202 the current hour. As also remarked in the literature [3,10], the number of interventions  
 203 on previous hours might impact ART. In addition, external data that may affect ART  
 204 were gathered from the following sources:

- 205 • Bison-Futé [29] provides prediction of traffic level for the Doubs region as indicators  
 206 ranging from 1 (regular flow) to 4 (extremely difficult flow) per day. We added  
 207 these indicators according to *SDate*;
- 208 • Météo-France [30] supplies historical weather information such as precipitation,  
 209 temperature, wind speed, and gust speed. We added weather data per hour accord-  
 210 ing to *SDate*;
- 211 • OSRM API [31] gives the driving distance on the fastest route and its travel time  
 212 duration. This way, with the coordinates from both *Center* and emergency's *Location*,  
 213 we added these two features, *i.e.*, estimated travel time in minutes and driving  
 214 distance in kilometers (km), for each ambulance.

#### 215 2.4. Data analysis

216 After removing outlying observations, the dataset at our disposal has 186,130 dis-  
 217 patched ambulances from SDIS 25 centers that attended 182,700 EMS interventions. The  
 218 frequency on the number of dispatched ambulances per zone is 39.62% (Z1), 33.38%  
 219 (Z2), 26.71% (Z3), and 0.29% (outside the Doubs region), respectively. Figure 1 illus-  
 220 trates the distribution of our variable of interest, namely ART, via three histograms  
 221 with bins of 1 minute for each zone within the Doubs region. One can notice that the  
 222 ART distributions follow a typical right-skewed distribution also observed in other  
 223 works/countries [3,27,32]. The mean and standard deviation (std) values for zones Z1,  
 224 Z2, and Z3 are  $8.79 \pm 5.66$  min,  $11.43 \pm 6.15$  min, and  $15.38 \pm 6.41$  min, respectively. SDIS  
 225 25 had about 79.52% of the time  $ART \leq 10$  min on zone Z1, and had about 95.76% and  
 226 92.50% of the time  $ART \leq 25$  min on zones Z2 and Z3, respectively.

227 Figure 2 illustrates the hourly number of dispatched ambulances (left-hand plot)  
 228 and the cumulative ART in hours per day of the week and hour in the day (right-hand  
 229 plot). One can notice that the number of dispatched ambulances is notably related to  
 230 the hour in the day, *i.e.*, there were more interventions in working periods rather than  
 231 between 0h to 6h. This behavior is also noticed in the works [11,27]. Besides, from 8h in

<sup>1</sup> [https://en.wikipedia.org/wiki/Great-circle\\_distance](https://en.wikipedia.org/wiki/Great-circle_distance)

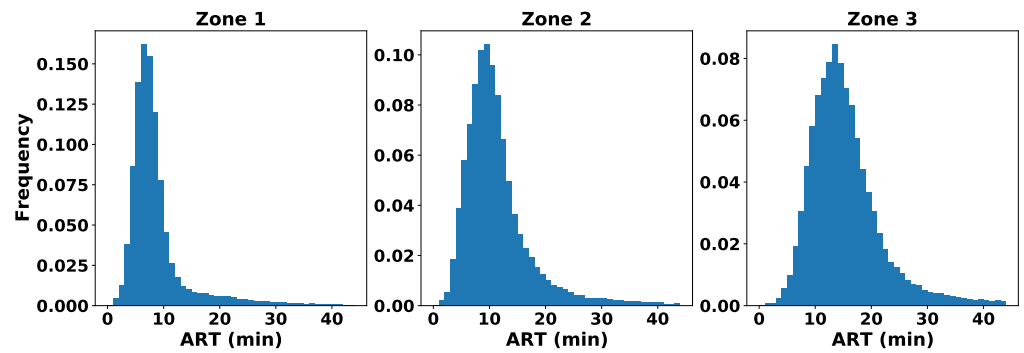


Figure 1. Distribution of the ART variable for zones Z1, Z2, and Z3, respectively.

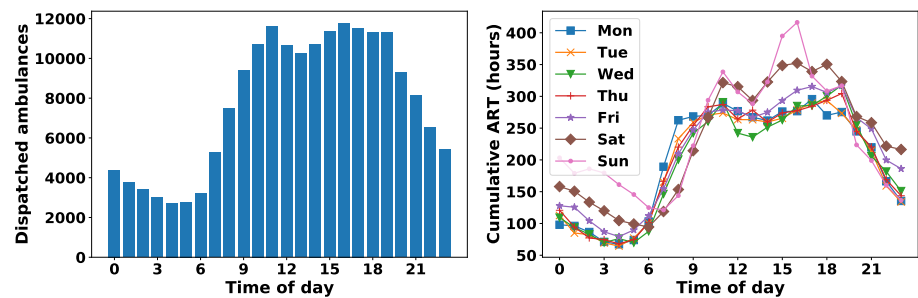


Figure 2. Histogram of the number of dispatched ambulances per hour in the day (left-hand plot) and cumulative ART in hours per day of the week and hour in the day (right-hand plot).

232 the morning on, the ART starts to increase and remains high up to 19h when it starts to  
 233 decrease. For instance, ambulances dispatched during working periods are more likely  
 234 to traffic congestion and, naturally, to undergo through longer travel time. Secondly, due  
 235 to the number of interventions in a given hour, SDIS 25 centers may have taken more  
 236 time to dispatch ambulances if their resources were in use in other incidents. A slightly  
 237 different profile can be seen on weekends, with noticeable higher cumulative ARTs in  
 238 the late night (0-6h) and during some hours of the day too.

239 Summary statistics per year and per zone are shown in Table 1. The metrics in this  
 240 table includes the total number of dispatched ambulances (Nb. Amb.), and descriptive  
 241 statistics such as mean and standard deviation (std) values for the ART variable. We  
 242 recall that for the year 2020, these statistics are up to June 2020 only. As also noticed  
 243 in [7,8], the number of interventions increases throughout the years. The year 2010  
 244 presented high values in comparison with all other years, *e.g.*, for Z1, the average ART  
 245 was above the 10 min recommendation.

### 246 2.5. Preserving emergency location privacy with geo-indistinguishability

247 To preserve the privacy of each emergency scene, we apply the polar Laplace  
 248 mechanism in Alg. 1 to the *Location* attribute of each intervention. This means, even  
 249 if our dataset is per ambulance dispatch (*i.e.*, 186,130 ambulances), we used the same  
 250 sanitized value per intervention (*i.e.*, 182,700 unique interventions). Although in [14] the  
 251 authors propose two further steps to Alg. 1, *i.e.*, discretization and truncation, both steps  
 252 can be neglected in our context. This is, first, because SDIS 25 may also help other EMS  
 253 outside the Doubs region as we discussed in Subsection 2.2, and second, we assume  
 254 that any location in the continuous plane can be an emergency scene. While reporting  
 255 an approximate location in the middle of a river may not have much sense in LBSs,  
 256 in an emergency dataset with approximate locations, this may indicate an urgency for  
 257 someone who drowned in the river, for example.

258 We used five different levels for the privacy budget  $\epsilon = l/r$ , where  $l$  is the privacy  
 259 level we want within a radius  $r$ . Table 2 exhibits the five different levels of privacy. For

Year	Z1			Z2			Z3		
	Nb. Amb.	Mean	Std	Nb. Amb.	Mean	Std	Nb. Amb.	Mean	Std
2006	197	9.23	4.41	367	11.25	5.50	354	14.27	5.40
2007	236	7.39	3.05	671	10.79	5.04	595	14.35	5.52
2008	799	8.69	6.04	1,055	11.19	5.32	911	14.53	6.02
2009	1,363	8.76	6.05	2,087	11.08	5.67	1,872	14.94	6.46
2010	2,643	10.08	7.23	2,797	12.48	6.85	2,483	16.01	7.22
2011	5,971	8.26	5.61	4,276	11.24	6.13	3,295	14.50	6.25
2012	6,078	8.66	5.89	4,661	11.18	6.39	3,602	14.86	6.24
2013	6,780	8.82	5.72	5,048	11.03	6.11	3,972	15.07	6.30
2014	6,847	8.37	5.23	5,481	10.80	5.86	4,240	14.91	6.34
2015	7,226	8.46	5.50	5,596	10.86	5.78	4,643	15.02	6.12
2016	7,510	8.50	5.35	6,179	11.19	5.92	4,861	15.32	6.35
2017	8,650	8.76	5.32	7,251	11.49	6.01	5,523	15.51	6.36
2018	9,051	8.90	5.46	7,641	11.64	6.11	5,956	15.59	6.23
2019	7,030	9.42	6.02	6,238	12.29	6.66	5,016	16.60	6.88
2020*	3,397	9.73	5.87	2,843	12.59	6.56	2,449	16.46	6.44

Table 1: Mean and std values for the ART variable and the total number of dispatched ambulances (Nb. Amb.) per year in zones Z1, Z2, and Z3, respectively. For 2020, we only consider cases of the first semester.

260 the sake of illustration, Figure 3 exhibits three maps of the Doubs region with the points  
 261 of original raw location (left-hand plot),  $\epsilon = 0.005493$ -GI location (middle plot), and  
 262  $\epsilon = 0.002747$ -GI location (right-hand plot). As one can notice, with an intermediate  
 263 privacy level ( $l = \ln(3), r = 400$ ), locations are more spread throughout the map while  
 264 with a lower privacy level ( $l = \ln(3), r = 200$ ), locations approximate the real clusters.

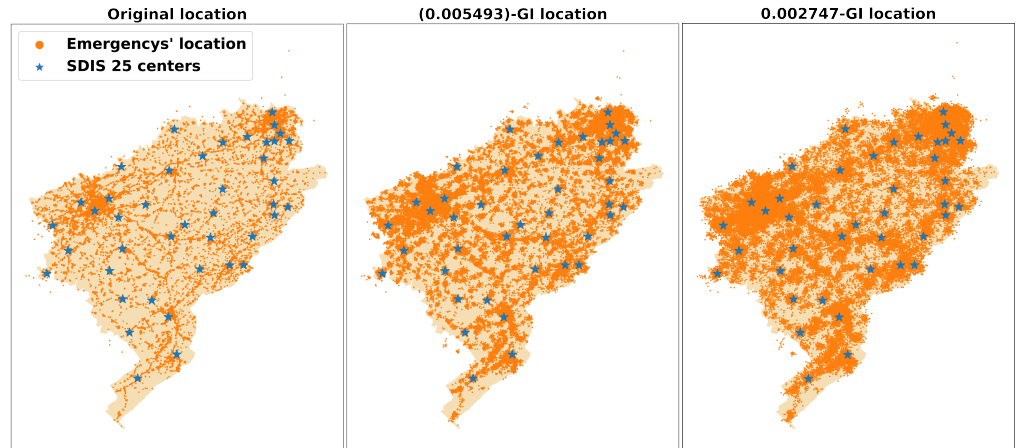
$\epsilon = l/r$	$l$	$r$ (meters)
0.005493	$\ln(3)$	200
0.002747	$\ln(3)$	400
0.001155	$\ln(2)$	600
0.000866	$\ln(2)$	800
0.000693	$\ln(2)$	1,000

Table 2: Values of  $\epsilon = l/r$  for sanitizing emergency location data with GI.

265 With the new *Location* values of each intervention, we also reassigned the city,  
 266 the district, and the zone when applicable. In addition, we recalculated the following  
 267 features associated with it: the great-circle distance, the estimated driving distance, and  
 268 estimated travel time. The two features recalculated with OSRM API only consider  
 269 roads, *i.e.*, if the obfuscated location is in the middle of a farm, the closest route estimates  
 270 the driving distance and travel time until the closest road. We also highlight that if the  
 271 new coordinates of the emergency scene indicate a location closer to another SDIS 25  
 272 center, even in real life, it would not imply that this center took charge of the intervention.  
 273 Therefore, the *center* attribute was not ‘perturbed’.

274 To show the impact of the noise added to the *Location* attribute, Table 3 exhibits the  
 275 percentage of time that categorical attributes (zone, city, and district) were ‘perturbed’  
 276 (*i.e.*, reassigned); the mean and std values of the great-circle distance attribute and its  
 277 correlation with the ART variable (Corr. ART). In Table 3, we report the mean(std)  
 278 values since we repeated our experiments with 10 different seeds (*i.e.*, DP algorithms are  
 279 randomized). Although we did not include the estimated driving distance and estimated  
 280 travel time from OSRM API in this analysis, in preliminary tests, we noticed that these  
 281 two features follow a similar pattern as the great-circle distance attribute.





**Figure 3.** Emergency locations and SDIS 25 centers throughout the Doubs region: original data (left-hand plot),  $\epsilon = 0.005493$ -GI data (middle plot), and  $\epsilon = 0.002747$ -GI data (right-hand plot).

282 From Table 3, one can notice that many features are perturbed due to sanitization  
 283 of emergency's location with GI. With high levels of  $\epsilon$  (*i.e.*, less private), the city and  
 284 the zone suffer low 'perturbation'. On the other hand, district is reassigned many times  
 285 as it is geographically smaller than the others. When  $\epsilon = 0.000866$ , the city is already  
 286 reassigned more than 50% of the time and the district about 75% of the time. Moreover,  
 287 one can notice that the mean and std values of the great-circle distance increase as the  
 288  $\epsilon$  parameter decreases (*i.e.*, more private). Because  $\epsilon = l/r$ , making  $l$  smaller and/or  $r$   
 289 higher, the stricter  $\epsilon$  becomes, and therefore more noise is added to the original locations.  
 290 Besides, the correlation between the great-circle distance with the ART variable decreases  
 291 proportionally as  $\epsilon$  becomes smaller.

Data	Zone	City	District	Great-circle Dist. (km)		
	'Perturbation' (%)			Mean	std	Corr. ART
Original	-	-	-	3.44	3.72	0.369
$\epsilon = 0.005493$	5.20(0.05)	7.68(0.06)	25.8(0.05)	3.48(1e-3)	3.72(7e-4)	0.367(2e-4)
$\epsilon = 0.002747$	11.3(0.05)	17.6(0.10)	41.5(0.12)	3.57(1e-3)	3.72(1e-3)	0.362(2e-4)
$\epsilon = 0.001155$	28.1(0.06)	42.3(0.10)	66.2(0.09)	4.03(3e-3)	3.74(3e-3)	0.335(5e-4)
$\epsilon = 0.000866$	35.5(0.10)	52.4(0.11)	74.0(0.11)	4.38(3e-3)	3.81(4e-3)	0.313(1e-3)
$\epsilon = 0.000693$	41.4(0.12)	60.3(0.09)	79.4(0.05)	4.77(6e-3)	3.92(5e-3)	0.288(1e-3)

Table 3: Percentage of perturbation for categorical attributes (city, zone, and district) according to  $\epsilon$  and statistical properties (mean and std values and correlation with ART) of the original and GI-based datasets for the great-circle distance attribute. Mean(std) values are reported since we repeated our experiments with 10 different seeds.

## 292 2.6. Machine learning models

293 Four state-of-the-art ML techniques have been considered during our experiments,  
 294 to predict the scalar ART outcome in a regression framework. They are briefly described  
 295 in the following:

- 296 • Extreme Gradient Boosting (XGBoost) [33] is a decision-tree-based ensemble ML  
 297 algorithm that produces a forecast model based on an ensemble of weak forecast  
 298 models (decision trees). XGBoost uses a novel regularization approach over stan-  
 299 dard gradient boosting machines, which significantly decreases model's complexity.  
 300 The system is optimized by a quick parallel tree construction and adapted to be  
 301 fault-tolerant under distributed environments.
- 302 • Light Gradient Boosted Machine (LGBM) [34] is a novel gradient boosting frame-  
 303 work, which implemented a leaf-wise strategy. This strategy significantly reduces

- 304 computational speed and resource consumption in comparison to other decision  
 305 tree-based algorithms.
- 306 • Multilayer Perceptron (MLP) is an artificial neural network of the feedforward  
 307 type [35]. These algorithms are based on the interconnection of several units  
 308 (neurons) to transmit signals, which are normally structured into three or more  
 309 layers, input, hidden(s), and output. We used the Keras library [36] to implement  
 310 our deep learning models.
  - 311 • Least Absolute Shrinkage and Selection Operator (LASSO), a method of contracting  
 312 the coefficients of the regression, whose ability to select a subset of variables is  
 313 due to the nature of the constraint on the coefficients. Originally proposed by  
 314 Tibshirani [37] for models using the standard least squares estimator, it has been  
 315 extended to many statistical models such as generalized linear models, etc. We  
 316 used the LASSO implementation from the Scikit-learn library [38].

### 317 2.7. Experiments

318 Because in Table 3 there are low variations (*i.e.*, small std values) considering 10  
 319 different executions on all analyzed features, we ran our experimental validation only  
 320 once. In our experiments, each sample corresponds to one ambulance dispatch, in  
 321 which we included temporal features (*e.g.*, hour, day), weather data (*e.g.*, pressure,  
 322 temperature), traffic data, the emergency's location (latitude and longitude in radians),  
 323 and computable features (*e.g.*, distance, travel time). The scalar target variable is the ART  
 324 in minutes, which is the time measured from the EMS notification to the ambulance's  
 325 arrival on-scene. All numerical features (*e.g.*, temperature) were standardized using the  
 326 *StandardScaler* function from the Scikit-Learn library. Categorical features (*e.g.*, center,  
 327 zone, hour) were encoded using mean encoding, *i.e.*, the mean value of the ART variable  
 328 with respect to each feature. The target variable, namely ART, was kept in its original  
 329 format (minutes) since no remarkable improvement was achieved with scaling.

330 We divided our dataset into training (years 2006-2019) and testing (six months of  
 331 2020) sets to evaluate our models. Thus, five models per ML technique (*i.e.*, XGBoost,  
 332 LGBM, MLP, and LASSO) were built to predict ART on each month of 2020 considering  
 333 the sanitized datasets with different levels of  $\epsilon$ -GI location data (*cf.* Table 2). In addition,  
 334 for comparison, we also trained one additional model per ML technique with original  
 335 raw data. All models were trained continuously, *i.e.*, at the end of each month, the new  
 336 known data were added to the training set. Lastly, **all models were tested with original**  
 337 **raw data as it would be if EMS deployed a decision-support system in real life.** In this  
 338 paper, the models were evaluated using the following regression metrics:

- 339 • Root mean squared error (RMSE) measures the square root average of the squares  
 340 of the errors and is calculated as:  $RMSE = \frac{1}{n} \sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2}$ ;
- 341 • Mean absolute error (MAE) measures the averaged absolute difference between  
 342 real and predicted values and is calculated as:  $MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$ ;
- 343 • Mean absolute percentage error (MAPE) measures how far the model's predictions  
 344 are off from their corresponding outputs on average and is calculated as:  $MAPE =$   
 345  $\frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \cdot 100\%$ ;
- 346 • Coefficient of determination ( $R^2$ ) measures the proportion of the variance in the  
 347 dependent variable that is predictable from the independent variable(s). An  $R^2 = 1$   
 348 would indicate a model that fully captures the variation in ARTs;

349 in which  $y_i$  is the real output,  $\hat{y}_i$  is the predicted output, and  $n$  is the total number of  
 350 samples, for  $i \in [1, n]$ . Results for each metric were calculated considering the 6 months  
 351 period of evaluation. The RMSE metric was also used during the hyperparameters  
 352 tuning process via Bayesian optimization (BO). To this end, we used the HYPEROPT  
 353 library [39] with 100 iterations for each model. Table 4 in Appendix A displays the range

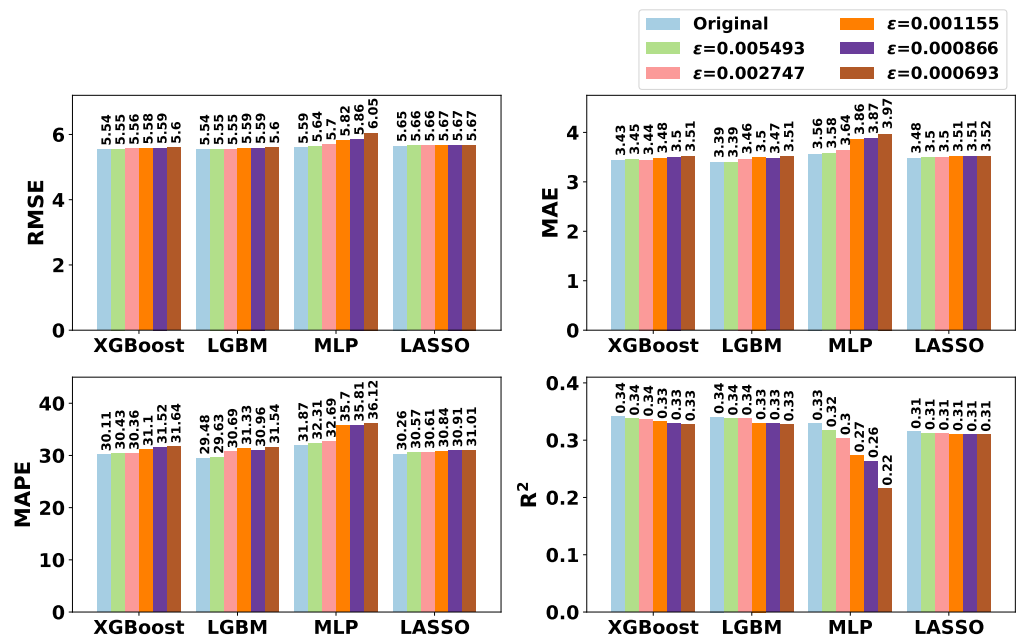
354 of each hyperparameter we considered in the BO, as well as the final configuration used  
 355 to train and evaluate the models.

### 356 3. Results and Discussion

357 In this section, we present the results of our experimental validation (Subsection  
 358 3.1) and a general discussion (Subsection 3.2) including related work and limitations.

#### 359 3.1. Privacy-preserving ART prediction

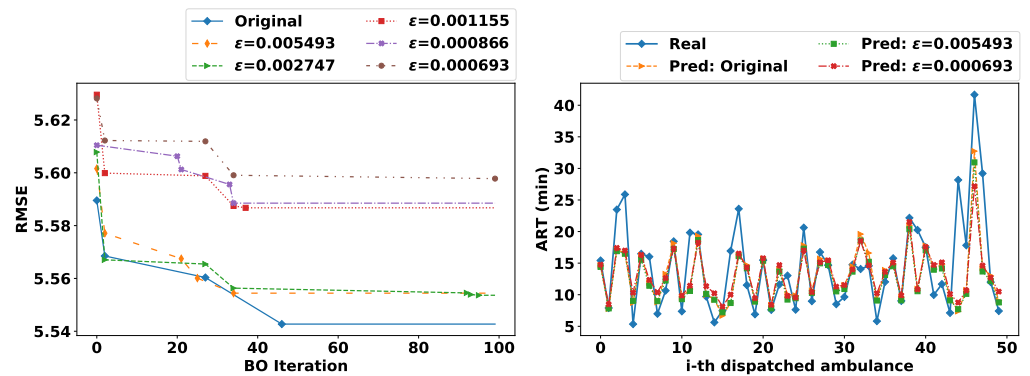
360 Figure 4 illustrates the impact of the level of GI for each ML model to predict ART  
 361 according to each metric. As one can notice in this figure, for XGBoost, LGBM, and  
 362 LASSO, there were minor differences between training models with original location  
 363 data or sanitized ones. On the other hand, models trained with MLP performed poorly  
 364 with GI-based data. In addition, by analyzing models trained with original data, while  
 365 the smaller RMSE for LASSO is about 5.65, for more complex ML-based models, RMSE  
 366 is less than 5.6, achieving 5.54 with XGBoost and LGBM. In comparison with the results  
 367 of existing literature, lower  $R^2$  scores and similar RMSE and MAE results were achieved  
 368 in [40] to predict ART while using original location data only. With more details, Table 5  
 369 in Appendix A numerically exhibits the results from Figure 4.



370 **Figure 4.** Impact of the level of  $\epsilon$ -geo-indistinguishability for each ML model to predict ART  
 371 according to each metric.

372 Indeed, among the four tested models, LGBM and XGBoost achieve similar metric  
 373 results while favoring the LGBM model. Thus, Figure 5 illustrates the BO iterative  
 374 process for LGBM models trained with original and sanitized data according to the  
 375 RMSE metric (left-hand plot); and ART prediction results for 50 dispatched ambulances  
 376 in 2020 out of 8,709 ones (right-hand plot) with an LGBM model trained with original  
 377 data (Pred: original) and with two LGBM models trained sanitized data, *i.e.*, with  
 378  $\epsilon = 0.005493$  (low privacy level) and with  $\epsilon = 0.000693$  (high privacy level).

379 As one can notice in the left-hand plot of Figure 5, once data are sanitized with  
 380 different levels of  $\epsilon$ -GI, the hyperparameters optimization via BO is also perturbed. This  
 381 way, local minimums were achieved in different steps of the BO (*i.e.*, the last marker per  
 382 curve indicates the local minimum). For instance, even though  $\epsilon = 0.002747$  is more  
 383 strict than  $\epsilon = 0.005493$ , results were still better for the former since, in the last steps  
 of BO, three better local minimums were found. Besides, prospective predictions were  
 achieved with either original or sanitized data. For instance, in the right-hand plot of



**Figure 5.** The left-hand plot illustrates the hyperparameters tuning process via Bayesian optimization with 100 iterations for LGBM models trained with original data and sanitized ones. The right-hand plot illustrates the prediction of ARTs with LGBM models trained with original data and with sanitized ones.

384 Figure 5, even for the high peak-value of ART around 40 minutes, LGBM's prediction  
 385 achieved some reasonable estimation. Although several features were perturbed due to  
 386 the sanitization of the emergency scene (*e.g.*, city, zone, etc), the models could still  
 387 achieve similar predictions as the model trained with original location data.

388 Lastly, in general, the most important features considering LASSO coefficients and  
 389 decision trees' importance scores were: OSRM API-based features (*i.e.*, estimated driving  
 390 distance and estimated travel time); the great-circle distance between the center and  
 391 the emergency scene; averaged ART per categorical features (*e.g.*, center, city, hour);  
 392 the number of interventions in the previous hour, and the number of interventions still  
 393 active.

### 394 3.2. Discussion

395 The medical literature has mainly focused attention on the analysis of ART [3,32,  
 396 41] and its association with trauma [2,28] and cardiac arrest [1,4,6], for example. To  
 397 reduce ART, some works propose reallocation of ambulances [5,42], operation demand  
 398 forecasting [5,7,8,19,43], travel time prediction [11], simulation models [27,44], and EMS  
 399 response time predictions [11,40]. The work in [40] propose a real-time system for  
 400 predicting ARTs for the San Francisco fire department, which closely relates to this paper.  
 401 The authors processed about 4.5 million EMS calls considering original raw location  
 402 data to predict ART using four ML models, namely linear regression, linear regression  
 403 with elastic net regularization, decision tree regression, and random forest. However, no  
 404 privacy-preserving experiment was performed because the main objective of their paper  
 405 was proposing a scalable, ML-based, and real-time system for predicting ART. Besides,  
 406 we also included weather data that the authors in [40] did not consider in their system,  
 407 which could help to recognize high ARTs due to bad weather conditions, for example.

408 Currently, many private and public organizations collect and analyze data about  
 409 their associates, customers, and patients. Because most of these data are personal  
 410 and confidential (*e.g.*, location), there is a need for privacy-preserving techniques for  
 411 processing and using these data. Location privacy is an emergency research topic [12,13]  
 412 due to the ubiquity of LBSs. Within our context, sharing and/or publishing the exact  
 413 location of an emergency raises many privacy issues. For instance, the Seattle Fire  
 414 Department [45] displays live EMS response information with the precise location and  
 415 reason for the incident. While the intention of some fire departments [40,45] is laudable,  
 416 there are many ways for (mis)using this information, which can jeopardize users' privacy.  
 417 In our case, because the intervention's *reason* does not impose limits on SDIS 25 ARTs,  
 418 we did not consider this sensitive attribute in our data analysis and privacy-preserving  
 419 prediction models. Additionally, although during the EMS call processing, the SDIS 25

operator may acquire some personal data about the *victim*, this is not an operational requirement and, hence, we did not use this information too. This way, we focused our attention on the *location privacy* of each intervention.

To address location privacy, the authors in [14] proposed the concept of GI, which is based on a generalization [26] of the state-of-the-art DP [15] model. As highlighted in [14], attackers in LSBs may have side information about the user's reported location, *e.g.*, knowing that the user is probably visiting the Eiffel Tower instead of swimming in the Seine river. However, this does not apply in our context because someone may have drowned and EMS had to intervene. Similarly, even for the dataset with intermediate privacy (and higher) in which locations are spread out in the Doubs region (*cf.* map with 0.005493-GI location in Figure 3), someone may have been lost in the forest and EMS would have to interfere. For these reasons, sharing datasets with approximate emergency locations (*i.e.*, sanitized with GI, for example) has prospective directions as many locations are possible emergency scenes. Indeed, we are not interested in hiding the emergency's location completely since some approximate information is required in order to retrieve other features (*e.g.*, city, zone, estimated distance) to use for predicting ART.

Moreover, learning and extracting meaningful patterns from data, *e.g.*, through ML, play a key role in advancing and understanding several behaviors. However, on the one hand, storing and/or sharing raw personal data with trusted curators may still lead to data breaches [46] and/or misuse of data, which compromises users' privacy. On the other hand, training ML models with raw data can also leak private information. For instance, in [47] the authors evaluate how some models can memorize sensitive information from the training data, and in [48], the authors investigate how ML models are susceptible to membership inference attacks. To address these problems, some works [7,17–22,49] propose to train ML models with sanitized data, which is also known as input perturbation [23].

Input perturbation-based ML and GI are linked directly with local DP [23] in which each sample is sanitized independently, either by the user during the data collection process or by the trusted curator, which aims to preserve privacy of each data sample. This way, data are protected from data leakage and are more difficult to reconstruct, for example. In [20,49], the authors investigate how input perturbation through applying controlled Gaussian noise on data samples can guarantee  $(\epsilon, \delta)$ -DP on the final ML model. This means, since ML models are trained with perturbed data, there is a perturbation on the gradient and on the final parameters of the model too.

In this paper, rather than Gaussian noise, the emergency scenes were sanitized with Alg. 1, *i.e.*, adding two-dimensional Laplacian noise centered at the exact user location  $x \in \mathbb{R}^2$ . In addition, this sanitization also perturb other associated and calculated features such as: city, district, zone (*e.g.*, urban or not), great-circle distance, estimated driving distance, and estimated travel time (*cf.* Table 3). As well as the optimization of hyperparameters, *i.e.*, once data are differentially private, one can apply any function on it and, therefore, we also noticed perturbation on the BO procedure. Yet, as shown in the results, prospective ART predictions were achieved with either original or sanitized data. What is more, even with a high level of sanitization ( $\epsilon = 0.000693$ ) there was a good privacy-utility trade-off. According to [50], if the mean absolute percentage error (*i.e.*, MAPE) is greater than 20% and less than 50%, the forecast is reasonable, which is the results we have in this paper with MAPE around 30%.

Lastly, some limitations of this work are described in the following. We analyzed ARTs using the data and operation procedures of only one EMS in France, namely SDIS 25. Although it may represent a sufficient amount of samples, other public and private organizations are also responsible for EMS calls, *e.g.*, the SAMU (Urgent Medical Aid Service in English) analyzed in [44]. Besides, there is the possibility of human error when using the mechanical system to report (*i.e.*, record) the arrival on-scene time "*ADate*". For instance, the crew may have forgotten to record status on arrival and may have

474 registered later, or conversely, where the crew may have accidentally recorded before  
475 arriving at the location. Also, it is noteworthy to mention that the arrival on-scene does  
476 not mean arriving at the victim's side, *e.g.*, in some cases the real location of a victim is  
477 at the  $n$ -th stage of a building as investigated in [41].

#### 478 4. Conclusion

479 In the event of an acute medical event such as a respiratory crisis or cardio-  
480 respiratory arrest, the time an ambulance takes to arrive on-scene has a direct impact on  
481 the quality of service provided [1,2,4–6,28]. Ambulance response time is a fundamental  
482 indicator of the effectiveness of EMS systems. For this reason, an intelligent decision-  
483 support system is necessary to help minimize overall EMS response times. The present  
484 work first analyzes historical records of ARTs to find correlations between their extracted  
485 features and explain the trends through the 15 years of collected data. Then, we sought  
486 to predict the response time that each center equipped with ambulances had to an event,  
487 but not only that, because we also consider that sharing or making public the location  
488 of the emergency would be subject to privacy issues. Therefore, the joint work aimed  
489 to evaluate the effectiveness of predicting ARTs considering ML models trained over  
490 sanitized location data with different levels of  $\epsilon$ -geo-indistinguishability. As shown in  
491 the results, the sanitization of location data and the perturbation of its associated features  
492 (*e.g.*, city, distance) had no considerable impact on predicting ART. With these findings,  
493 EMS may prefer using and/or sharing sanitized datasets to avoid possible data leakages,  
494 membership inference attacks, or data reconstructions, for example.

495 For future work, we aim to extend the analysis and predictions to different operation  
496 times such as the pre-travel delay (*i.e.*, gathering personnel and ambulances) and travel  
497 time (*e.g.*, from the emergency scene to hospitals), while respecting users' privacy. In  
498 addition, new variables will be considered such as the number of dispatched ambulances  
499 registered in a previous or current time, and the number of ambulances and firefighters  
500 available in each center at a given time, given that while there are few resources available,  
501 ART may be longer. Indeed, the aim is to build an intelligent system capable of predicting  
502 ARTs while respecting victims' privacy. This way, this system would allow us to reinforce  
503 SDIS 25 centers with the necessary firefighters to attend incidents faster; to create a new  
504 center according to the concurrence and high average ARTs for a given area; as well  
505 as to convert a static resource deployment plan into a dynamic one, which would be  
506 based on the selection of the center with shorter response times taking into account the  
507 community the emergency took place, traffic and weather conditions, and so on.

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509 ware, H.H.A and S.C.; validation, H.H.A and S.C.; formal analysis, H.H.A and S.C.; investigation,  
510 H.H.A, S.C., C.G., and J.F.C.; resources, C.G. and J.F.C.; data curation, H.H.A and S.C.; writing—  
511 original draft preparation, H.H.A., S.C., C.G., and J.F.C.; writing—review and editing, H.H.A., S.C.,  
512 C.G., and J.F.C.; visualization, S.C. and C.G.; supervision, C.G. and J.F.C.; project administration,  
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## 526 Abbreviations

527 The following abbreviations are used in this manuscript:

528	Ambulance response time	ART
	Bayesian optimization	BO
	Differential privacy	DP
	Emergency medical services	EMS
	Geo-Indistinguishability	GI
	Least Absolute Shrinkage and Selection Operator	LASSO
	Location-based services	LBSs
	Local differential privacy	LDP
	Light Gradient Boosted Machine	LGBM
529	Multilayer Perceptron	MLP
	Mean absolute error	MAE
	Mean absolute percentage error	MAPE
	Root mean squared error	RMSE
	Departmental Fire and Rescue Service of Doubs	SDIS 25
	Extreme Gradient Boosting	XGBoost
	Zone urban	Z1
	Zone semi-urban	Z2
	Zone rural	Z3

## 530 Appendix A. Complementary Results

Model	Search space	Best configuration per dataset					
		Original	$\epsilon = 0.005493$	$\epsilon = 0.002747$	$\epsilon = 0.001155$	$\epsilon = 0.000866$	$\epsilon = 0.000693$
XGBoost	max_depth: [1, 10]	9	9	6	6	9	9
	n_estimators: [50, 500]	465	465	130	235	465	465
	learning_rate: [0.001, 0.5]	0.0265	0.0265	0.0858	0.0486	0.0265	0.0265
	min_child_weight: [1, 10]	5	5	7	7	5	5
	max_delta_step: [1, 11]	4	4	3	4	4	4
	gamma: [0.5, 5]	3	3	0	2	3	3
	subsample: [0.5, 1]	0.8	0.8	1	1	0.8	0.8
	colsample_bytree: [0.5, 1]	0.5	0.5	0.5	0.5	0.5	0.5
	alpha: [0, 5]	2	2	1	2	2	2
LGBM	max_depth: [1, 10]	7	8	10	8	8	6
	n_estimators: [50, 500]	355	326	477	250	80	441
	learning_rate: [1e-4, 0.5]	0.0188	0.0098	0.0164	0.0285	0.0586	0.0300
	subsample: [0.5, 1]	0.54066	0.5228	0.6138	0.6699	0.6732	0.5812
	colsample_bytree: [0.5, 1]	0.5160	0.5575	0.5204	0.6870	0.5507	0.5451
	num_leaves: [31, 400]	400	192	245	398	132	95
	reg_alpha: [0, 5]	4	0	5	0	1	4
MLP	Dense layers: [1, 7]	7	3	4	6	6	6
	Number of neurons: [2 <sup>8</sup> , 2 <sup>13</sup> ]	2 <sup>10</sup>	2 <sup>12</sup>	2 <sup>12</sup>	2 <sup>9</sup>	2 <sup>12</sup>	2 <sup>9</sup>
	Batch size: [32, 168]	140	80	48	82	70	44
	Learning rate: [1e-5, 0.01]	0.00265	0.00124	0.0099	0.0099	0.0094	0.0077
	Optimizer: Adam	Adam	Adam	Adam	Adam	Adam	Adam
	Epochs: 100	100	100	100	100	100	100
	Early stopping: 10	10	10	10	10	10	10
LASSO	alpha: [0.01, 2]	0.0205	0.0307	0.0105	0.0100	0.0112	0.0107

Table 4: Search space for hyperparameters by ML model and the best configuration obtained for predicting ARTs per dataset.

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Data	Metric	XGBoost	LGBM	MLP	LASSO
Original	RMSE	<b>5.5398</b>	5.5427	5.5916	5.6511
	MAE	3.4286	<b>3.3880</b>	3.5623	3.4760
	MAPE	30.114	<b>29.476</b>	31.867	30.260
	R <sup>2</sup>	<b>0.3412</b>	0.3405	0.3289	0.3145
$\epsilon = 0.005493$	RMSE	5.5547	<b>5.5544</b>	5.6401	5.6596
	MAE	3.4515	<b>3.3915</b>	3.5773	3.4960
	MAPE	30.432	<b>29.628</b>	32.307	30.571
	R <sup>2</sup>	0.3377	<b>0.3378</b>	0.3172	0.3124
$\epsilon = 0.002747$	RMSE	5.5617	<b>5.5536</b>	5.6959	5.6636
	MAE	<b>3.4430</b>	3.4628	3.6357	3.4991
	MAPE	<b>30.364</b>	30.688	32.687	30.606
	R <sup>2</sup>	0.3360	<b>0.3379</b>	0.3036	0.3115
$\epsilon = 0.001155$	RMSE	<b>5.5788</b>	5.5867	5.8184	5.6671
	MAE	<b>3.4803</b>	3.4991	3.8550	3.5094
	MAPE	31.097	31.327	35.704	<b>30.835</b>
	R <sup>2</sup>	<b>0.3319</b>	0.3300	0.2733	0.3106
$\epsilon = 0.000866$	RMSE	5.5892	<b>5.5885</b>	5.8575	5.6716
	MAE	3.5033	<b>3.4702</b>	3.8736	3.5134
	MAPE	31.515	30.964	35.810	<b>30.907</b>
	R <sup>2</sup>	0.3295	<b>0.3296</b>	0.2635	0.3095
$\epsilon = 0.000693$	RMSE	<b>5.5962</b>	5.5978	6.0463	5.6717
	MAE	3.5119	<b>3.5087</b>	3.9704	3.5171
	MAPE	31.638	31.543	36.122	<b>31.007</b>
	R <sup>2</sup>	<b>0.3278</b>	0.3274	0.2153	0.3095

Table 5: Metrics results for each ML model trained with original data and sanitized ones. The best results per metric and model are highlighted in bold.

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