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Philippe Jacquet. The Ariadne String against Covid-19 pandemic propagation during lock-downs. 2020. hal-02546347v2

HAL Id: hal-02546347

<https://hal.science/hal-02546347v2>

Preprint submitted on 27 Apr 2020

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The Ariadne String against Covid-19 pandemic propagation during lock-downs

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Abstract— We present the Ariadne String against Covid application, whose aim is to recommend safe outdoor path inside cities in order to limit the exposure to virus propagation. The main idea is to make a load balancing between streets via space-time diversity. The application is shown to be efficient at the very first user, and lead to an optimal Nash equilibrium when there is a majority of user. We have tried a performance analysis over prior lock-down pedestrian traffic estimates over Paris, Manhattan and Rome. It is shown that application reduces the user exposure cumulative time by a factor 3.

I. INTRODUCTION AND MOTIVATION

The main issue in fighting a pandemic virus propagation is the limitation and reduction of contact between susceptible people and infected people, in particular during lock-down period.

Since the exceptionally long incubation period of Covid-19, it is in general difficult to distinguish between infected and susceptible people. Therefore lockdown periods have been set in most part of the planet in order to limit the contacts between people in the ignorance of their status (infected, susceptible, immunized).

The virus Covid-19 is supposed to have some probability to be transferred when an infected person is within 1 m of another person during a certain time. The larger is this time the higher will be the probability (for very infected people it is around 30 mn). Therefore we call "contact" the event when two persons are within 1m of each other. We call exposure cumulation the cumulated time a person is within 1m of any other person monitored during a certain interval time. We call exposure rate the fraction of the cumulated time divided by the total monitored time. We call outdoor exposure, the exposure during contact happening in outdoor situation.

Now (early April 2020) a large part of mankind is under institutional lock-down to slow down the propagation. In Europe and in the US most of the countries have adopted a flexible lock-down where people are allowed a daily derogative excursion outside their home. In France it is currently one excursion of one hour per day within a radius of one kilometer from home.

The problem with this kind of lock-down is that walkers (or jogger) shows a *social* trend to gather in the same streets, making the exposure rate still too high. We have no data after lock-down start, but data sampled via Google Street View show that the social trends have indeed an impact on exposure

rate. We don't know if the social trends have the same profile as before the lock-down but it is probably very similar, to the exception of commercial areas which may become less attractive than parks or riverbanks or sea sides. Recently administrative authorities have closed the access to sea, river and forests in order to avoid gathering in this place, with the consequence of limiting again the path-length devoted to pedestrians or joggers. In the paper we will call *social walkers* (or social joggers) the pedestrian who follows the social trends in the outdoor excursion in the city.

The mythological heroin Ariadne offered Theseus a string in order to fight Minotaur in the Labyrinth. The idea of our modern Ariadne is to offer a numerical string for the walker in the city, not to fight Minotaur, but to avoid the exposure to the coronavirus.

There are 2,900 km of cumulative pedestrian path length in Paris for a population of 2.2 million inhabitants [1], [2]. Therefore there is ample room for all of the inhabitants to walk 24/24h within safe distance. Since only a fraction of the inhabitant are expected to be walking at the same time, it should be easy to get the safe spacing.

To get the safe spacing or minimizing the exposure rate we propose the Ariadne Covid application concept. Its aim is to make a load balancing over street via random walks. That way if all walkers and jogger are using the application, we get the optimal density over the streets namely the uniform distribution. Furthermore, if the Ariadne String against Covid application user are not in majority, each of the user will get an exposure reduction even larger than if all the population was using the application. In fact the advantage is given as soon as there one Ariadne Covid user. It can be shown that Ariadne Covid can in theory reduce the exposure time by a factor 3. Of course in order to have an impact on the propagation of the epidemy there would be a need for a majority of user, but at least each user will get a tangible advantage by reducing the exposure at the very beginning. This is like a Nash optimal equilibrium, the aim of the Ariadne Covid application is break the lethal social trend in street gathering.

The plan of this paper is the following. In section II we describe the Ariadne Covid application: its embedded component on smartphone and its server component. The section III describes the model and theoretical aspects and their application city data such as Paris, Manhattan and Rome. Since the city data are prior to lock-down, a steeper projection

of lock-down data has been extrapolated under the title Paris Zipf 1.

II. ARIADNE STRING PROTOCOL DESCRIPTION

The application consists into delivering to the user who requests it, a random path for the excursion and the time slot in the day. This path will avoid the dangerous areas in proportion of the risks (not necessarily due to the virus, *i.e.* accident, fire, or work areas), or the areas with an actual density due to people at regular work or still submitted to their social tendencies. In its most basic setting the path will be purely random, since it has been shown to actually reduce the exposure rate even if the user is alone in Paris to do that. Indeed it is shown that the exposure is even more reduced compared to the situation where all Parisians would use the application Ariadne Covid.

During the excursion the user will have his/her own position displayed on her/his mobile phone. (S)he may receive vocal indications and receive warning when the walker leaves the path. At half of the time the walker will receive an alert asking to reverse the path (the only way to keep path uniformization). The path may contain loops, because it is necessary in order to get the uniform density. If it is the case the walker will proceed with the loop. The walker may skip the loop in the way back but this will shorten the delay of the excursion, thus (s)he would be better proceed again with the loop in the way back.

The application terminates (at least its embedded mobile part) when the user is back home.

A. Description of the algorithm in the mobile embedded part

The user should have to register to the server part, to request for a path the user will login and enter a time schedule with a reasonably large time span when (s)he can have its excursion scheduled that day. In particular the user should enter its own street address if the data is not included in the registration data or if it differs. Equivalently, at the choice of the user the embedded part of the application could directly send to the server the GPS coordinate of the phone. The server will compute and return a time slot, a path, and an advised excursion duration to be displayed on the smartphone.

If there is time before the excursion, the application will deactivate to save battery. The user will reactivate the application at the time of the excursion. The application will display a map with the path together with the tracking of the position of the smartphone.

During the excursion the user will have his/her own position displayed on her/his mobile phone. (S)he may receive vocal indications and receive warning when the walker leaves the path. At half of the time the walker may receive an alert asking to reverse the path. It must be noted that none of these warning and alerts will be returned to the server to preserve the privacy, they could also be disabled if the user wants to. The path may contain loops, if it is the case the walker will proceed with the loop. Thus, the display should be adapted to show segment (eg next segment) to make readable the path during loops. The

walker may skip the loop in the way back but this will shorten the delay of the excursion, thus (s)he would rather proceed again with the loops in the way back.

B. Description of the application on the server side

When the server receives the request from the user, it first project the initial position on the main local component of the google street map network (a priori pre-processed for once). Then from this position it computes the random path. The random path will larger than needed because we don't know *a priori* if the excursion will be for walking or jogging. The random walk should be extended to a maximum length (*e.g.* 5km).

1) *Computation of the excursion time slot:* The time slot is selected uniformly on the time schedule proposed by the user in his/her request. If recurrent district pedestrian density or risk information is available, the time slot selection will take into account the information to make more likely the time slots with lower density and risk.

2) *Computation of the random walk:* The first step is to randomly select the initial direction: left or right with probability $1/2$, $1/2$ on the street of the home address. Until five kilometers is attained the algorithm proceed to the determination of the random walk.

a) *Non-backtracking algorithm:* at each intersection the algorithm randomly selects the exit road excluding the current street. If the intersection has four roads, thus three eligible exits, the weight of each exit is $1/3$, $1/3$, $1/3$. In case of dead-end, the algorithm selects the U turn. This guarantees the uniformisation of the densities

If the cartesian distance to home address exceeds the authorized distance from home (1km in France), the path should make a U-turn.

b) *Non backtracking algorithm with reduced path diversions:* if the intersection has an even number of streets (thus an odd number of exits) more weight will be given to the exit street facing the entry street, *i.e.* the median exit. For example, the median exit has $1/2$ probability to be selected, and the other exit are selected uniformly. This keep the uniformization of the densities.

c) *Further options:* when density or risk factor is available at street level, the weight of the exit streets at each intersection could be made non uniform. In this case the weight should be adapted to make the risk identical for each street (by reducing the density). The non-backtracking random path calculation would need to be adapted in order to cope with this situation.

3) *Advised excursion time duration:* At the time of the excursion, the excursion duration should be advised according to up to date density and risk information, in order to make it equivalent to one hour of virus exposure in normal situation.

a) *Remark:* it could be made larger than one hour, if densities and risk are low and if legislation allows it.

III. PERFORMANCE ANALYSIS OF THE ARIADNE STRING AGAINST COVID

We split the whole pedestrian path into a segment set \mathcal{S} . A segment $s \in \mathcal{S}$ at time t has a linear density $\lambda(s, t)$ and a length $\ell(s)$. The total length of the pedestrian network is $L = \sum_{s \in \mathcal{S}} \ell(s)$. The total pedestrian population at time t is $N(t) = \sum_{s \in \mathcal{S}} \lambda(s, t) \ell(s)$. The probability that a pedestrian walk on segment s at time t is $\rho(s, t) = \frac{\ell(s) \lambda(s, t)}{N(t)}$. If we assume that the distribution on every segment is uniform (and ignoring side effects) the probability that a given pedestrian on segment s is within distance r to another given pedestrian on the same segment is $\frac{2r}{\ell(s)}$ which could be reduced to $\frac{r}{\ell(s)}$ if the dangerous zone stands forward to the pedestrian.

Thus if a total population of N pedestrians are present on the streets, each independently following the density pattern of the $\lambda(s, t)$, the probability that a pedestrian on segment s is not on situation of contact at time t is $\left(1 - \rho(s, t) \frac{2r}{\ell(s)}\right)^N$ or equivalently $\left(1 - 2r \frac{\lambda(s, t)}{N(t)}\right)^N$.

Let N_T the total population of the city. If the proportion of inhabitants walking outdoor is ν , the average exposure rate $E_G(\nu)$ satisfies

$$E_G(\nu) = 1 - \sum_{s \in \mathcal{S}} \rho(s) \left(1 - \rho(s) \frac{2r}{\ell(s)}\right)^{\nu N_T}. \quad (1)$$

assuming that $\rho(s) := \rho(s, t)$ does not vary (too much) during the day. If $\rho(s, t)$ varies during the day and $\rho(s)$ is its average on segment s , then by concavity the above expression is an upper bound of the exposure rate.

We have sampled 55 km of Paris street via Google Street View. We have made 11 independent random walks starting in different *arrondissement*. A segment (30 m) of pedestrian path is sampled every 100 m. Figure 1 the histogram of segment densities sampled in Paris. The Street View pictures date before the lockdown, and mixe several periods belonging to different months and years, sometimes the switches occur in the same street. Anyhow the histogram shows a profile close to a Zipf distribution of coefficient around 0.75. We have no yet records for the period during the lockdown, but we expect a more concentrated distribution with a larger Zipf coefficient, since the most of the commercial areas are closed and therefore attraction streets are reduced.

First we prove that the random walk correctly balances the loads among the street

Theorem III.1. *The stationary distribution of the non-backtracking random walk is the uniform distribution density.*

By uniform distribution we mean that the average throughput in every street are identical.

Proof: This is mainly a state of the art result. Let consider a given intersection point A where m streets arrives with $m > 1$. We assume that at time t every street input rate at intersection A are all identical to x , we will show that the input rate are also all identical to x , and thus the steady state

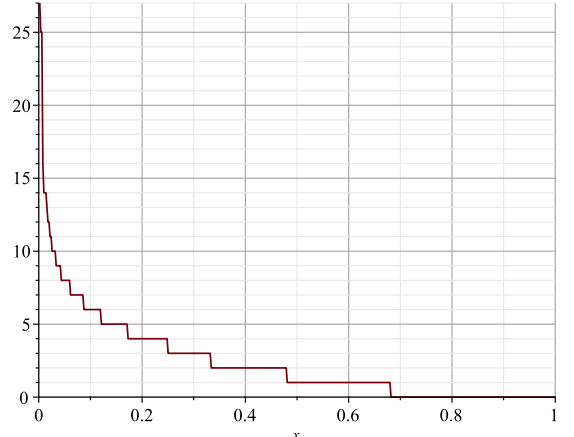


Fig. 1: Histogram of Pedestrian densities in Paris

distribution are all uniform. Indeed each street contributes to $\frac{x}{m-1}$ other streets, since the random walk divert to the other streets with equal probabilities. Therefore each street receives input from all streets except itself, equal to $(m-1) \frac{x}{m-1} = x$.

When $m = 1$ (dead-end) the random walk backtracks and the property is preserved.

But the random walk steady state may be long to converge. In our case it is faster because the density of inhabitant in Paris is almost uniform along each street, thanks to Hausmannian construction rules dating from the XIXth century [3]. From now we take the simplified assumption that walker using the random walk are indeed in uniform density in the streets.

Let $E_U(\nu)$ be the average exposure rate when all walkers are in random walk situation. It satisfies:

$$E_U(\nu) = 1 - \left(1 - \frac{2r}{L}\right)^{\nu N_T}. \quad (2)$$

Indeed it suffices to consider the whole pedestrian network as a single segment.

More interestingly we have the case when a single random walker proceeds among νN_T walkers following their social trends. Let's call $E_{UG}(\nu)$ her/his exposure rate:

$$E_{UG}(\nu) = 1 - \sum_{s \in \mathcal{S}} \frac{\ell(s)}{L} \left(1 - \rho(s) \frac{2r}{\ell(s)}\right)^{\nu N_T}. \quad (3)$$

We can generalize to $E_{UG}(\nu_U, \nu_G)$ to estimate the exposure rate of a random walker when the proportion of random walker is ν_U and the the proportion of social walker is ν_G , and conversely $E_{GU}(\nu_U, \nu_G)$ is the exposure of a social walker in the same conditions:

$$\begin{cases} E_{UG}(\nu_U, \nu_G) &= 1 - \left(1 - \frac{2r}{L}\right)^{\nu_U N_T} \\ &\quad \times \sum_{s \in \mathcal{S}} \frac{\ell(s)}{L} \left(1 - \rho(s) \frac{2r}{\ell(s)}\right)^{\nu_G N_T} \\ E_{GU}(\nu_U, \nu_G) &= 1 - \left(1 - \frac{2r}{L}\right)^{\nu_U N_T} \\ &\quad \times \sum_{s \in \mathcal{S}} \rho(s) \left(1 - \rho(s) \frac{2r}{\ell(s)}\right)^{\nu_G N_T} \end{cases} \quad (4)$$

We will not use these last two expressions.

In the following figures we display the performance of the random walk versus social walk. This apply also to jogging

since the average proportion of time spent to unsafe distance of people is the same in running or walking.

We assume that the Parisians have an interval of time (10 hour) where they can select their select their slot time for their outdoor excursion. The duration of the excursion is ν_0 expressed as a fraction of the whole 10 h interval.

The picture 2 shows the cumulative exposure rate as a fraction of 10 hour spend within unsafe distance to another individual. The solid red curves shows the cumulative exposure rate when all walkers are social walkers and they randomly select their slot on the whole 10 hours interval: this is the function $\nu E_G(\nu)$. The dashed red curve is when the social walkers have also time habit: they all select their time slot on an interval of 5 hours instead of 10 hours (*e.g.* the afternoon). This is the function $\nu E_G(2\nu)$ (for $\nu < 0.5$: 5 hours). The blue curve shows the cumulative exposure rate when all walkers are random walkers and they randomly select their slot on the whole 10 hours interval: this is the function $\nu E_U(\nu)$.

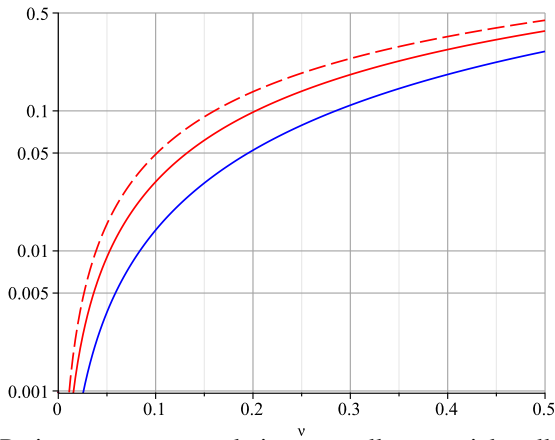


Fig. 2: Paris: exposure cumulative rate, all are social walkers but randomly dispatched on 10 hours (red), social walkers but concentrated on 5 hours (dashed red), all random walkers (blue) as function of the average outdoor excursion (in fraction of 10h)

The figure 3 shows the benefit when even only one user adopt the random walk. The red curve shows the cumulated exposure rate when a single social walker varies its excursion duration, but the other walkers are social and their average excursion time is 1 hour: this is the function $\nu E_G(0.1)$, this is just a linear function. The green curve is when the single user is a random walker: this is the function $\nu E_U(0.1)$. The random walker get some little more benefit compared with the situation when all walkers are random. In dashed when the other social walkers concentrates in five hours: these are respectively function $\nu E_G(0.2)$ in red and $\frac{\nu}{2} E_U(0.2)$ in green. The $1/2$ factors comes from the fact that the random walker has only a probability $1/2$ to select its excursion time during the 5 hours of the social walkers. Notice that the cumulative exposure rate is even smaller for the random walker.

The table I tries to summarize some important results, each

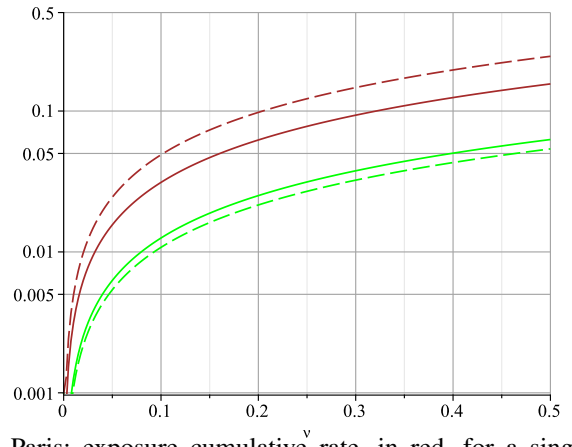


Fig. 3: Paris: exposure cumulative rate, in red, for a single walker in function of its excursion duration, when all other walkers are social walkers during 1 hour, in green when the single walker is random. In dashed when the social walkers select their slot on an interval of 5 hours

column gives the equivalent exposure time of 1 hour of three investigated modes: (i) all walkers are social, (ii) all walkers are random, (iii) one walker is random, the other are social. the first columns shows how much time the mode all social walker will provide an equivalent exposure cumulative rate. It is of course 1 hour for mode (i), since it is the same mode. It is 38 mn for mode (ii): to get an equivalent exposure if all walker are random during 1 hour, the social walkers should together limit their excursion to 38 mn. In mode (iii), to get the same exposure of one hour of a single random walker among all other social walker, each social walker should limit their excursion to 35 mn.

Conversely (last column, first line) to reach the exposure time of each social walker, the random walker could extend his/her excursion time to 2h14mn.

If (second column, last line) to get the exposure of a random walker walking 1 hour a social walker walking with other social walkers, will get the same exposure to virus before 24 mn.

The times in parentheses are the equivalent times when the social walkers are concentrated over 5h instead of 10 hours. For example (first column, first line) if the social walkers are concentrated on 5 hours, they will get the same exposure in 45 mn instead of 1 hour if the social walkers time slots are well distributed over 10 hours. One of these concentrated social walker will get in 17 mn the exposure of a random walker, or in 15 mn if the other walkers are non concentrated walkers (second column, second and third lines). Anyhow, for the perspective of the epidemie propagation, the interesting result is the reduction of exposure when a majority user adopt the new walking startegy and reduce the global contact rate. For Paris data, it turns out that the reduction is within a factor between 2.21 and 3.45, assuming one hour of walking. The first number is when social walkers excursion time slots are well distributed on the 10 hour time interval, and the second

columns: equivalent times	all social walkers	one variable social other 1 hour social	all random walkers	one variable random other 1 hour social
1 hour all social	1h (0h45mn)	1h (0h38mn)	1h30mn	2h14mn (2h53mn)
1 hour all random	38mn (28mn)	27mn (17mn)	1h	1h07mn (1h18mn)
1 hour random other social	35mn (26mn)	24mn (15mn)	56mn	1h (1h10mn)

TABLE I: Paris: per column, the equivalent exposure times for respectively 1 hour of all social walkers, of all random walkers, of one random walker, the other being social walkers. In parentheses when the social walkers are concentrated on 5 hours

numbers is when the social walkers are concentrated on 5 hours instead.

A. Manhattan, New York

We have extended the analysis to other cities. First example: Manhattan in New York City. Manhattan has 1.6 million inhabitants [5]. Its street cumulative length is 508 miles [4], thus a maximum of 1016 miles of pedestrian path, assuming that each street has two pedestrian path, which is not necessary the case for every street. We stress that the street cumulative length should include all streets of New York City, which is much larger than Manhattan, Notice that the cumulative length is shorter than in Paris. Maybe it is the reason why the parks and river banks are still allowed. The walker density has been sampled via eight random walks, with starting points uniformly selected over Manahattan map. However the analysis over Paris may not appliable, since New York does not follow the Hausmannian property of uniform linear density of habitants. Some district may have less habitant than other districts, *e.g* the business districts of lower Manhattan. The histogram is given in Figure 4. Figure 5 shows the exposure rate when all walkers are social or are all random. Figure 6 shows the exposition rates when a single walker is random.

For New York data, it turns out that the reduction exposition factor is between 2.05 and 3.1.

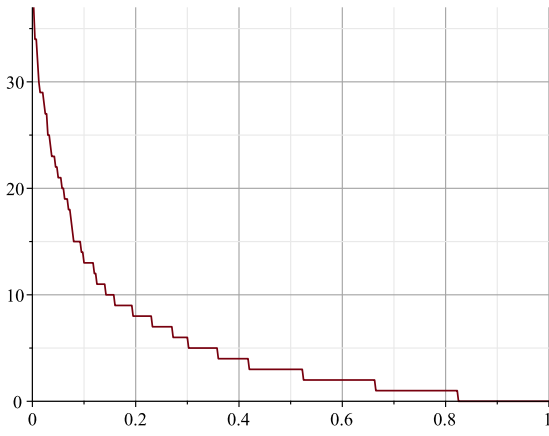


Fig. 4: Histogram of Pedestrian densities in Manhattan

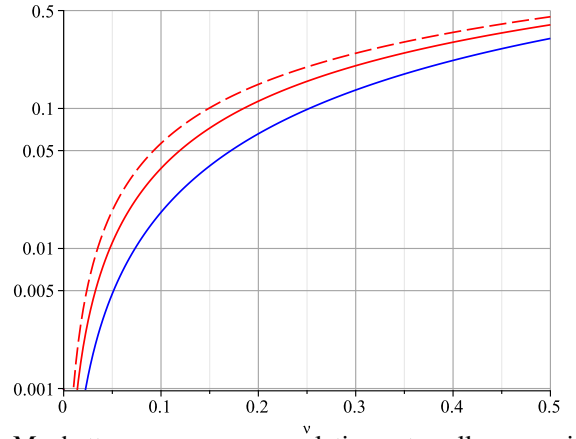


Fig. 5: Manhattan: exposure cumulative rate, all are social walkers but randomly dispatched on 10 hours (red), social walkers but concentrated on 5 hours (dashed red), all random walkers (blue) as function of the average outdoor excursion (in fraction of 10h)

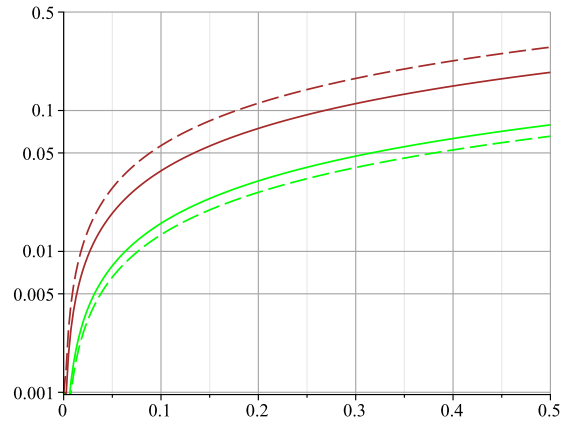


Fig. 6: Manhattan: exposure cumulative rate, in red, for a single walker in function of its excursion duration, when all other walkers are social walkers during 1 hour, in green when the single walker is random. In dashed when the social walkers select their slot on an interval of 5 hours

B. Rome

We have investigated Rome in our analysis. There 2.8 million inhabitant in Rome central. Unfortunately it has been very difficult to find credible data about the street cumulative length. Anyhow we have taken the data of Madrid [7] which, for an equivalent population, shows a total street length of 3,000 km, which is probably 6,000 km of pedestrian path. Given this large amount, the uniformization is expected to be the most efficient on the exposure time. The pedestrian histogram (see figure 10, has been established over eight independent random walk. Anyhow it should be noted that the districts show large variation in population density and street density, which would need a more careful study. The comparative effect of social and random walks are given in

columns: equivalent times	all social walkers	one variable social other 1 hour social	all random walkers	one variable random other 1 hour social
1 hour all social	1h (0h45mn)	1h (0h39mn)	1h28mn	2h14mn (2h50mn)
1 hour all random	39mn (29mn)	29mn (19mn)	1h	1h08mn (1h22mn)
1 hour random other social	36mn (27mn)	25mn (16mn)	55mn	1h (1h12mn)

TABLE II: Manhattan: per column, the equivalent exposure times for respectively 1 hour of all social walkers, of all random walkers, of one random walker, the other being social walkers. In parentheses when the social walkers are concentrated on 5 hours

columns: equivalent times	all social walkers	one variable social other 1 hour social	all random walkers	one variable random other 1 hour social
1 hour all social	1h (0h44mn)	1h (0h37mn)	1h40mn	2h17mn (3h19mn)
1 hour all random	34mn (25mn)	22mn (13mn)	1h	1h05mn (1h13mn)
1 hour random other social	32mn (24mn)	20mn (12mn)	57mn	1h (1h07mn)

TABLE III: Rome: per column, the equivalent exposure times for respectively 1 hour of all social walkers, of all random walkers, of one random walker, the other being social walkers. In parentheses when the social walkers are concentrated on 5 hours

figure 8, figure 9 and table III. It turns out that the reduction exposition factor is between 2.70 and 4.35 when all walkers are random walkers compared to the case when all walkers are social.

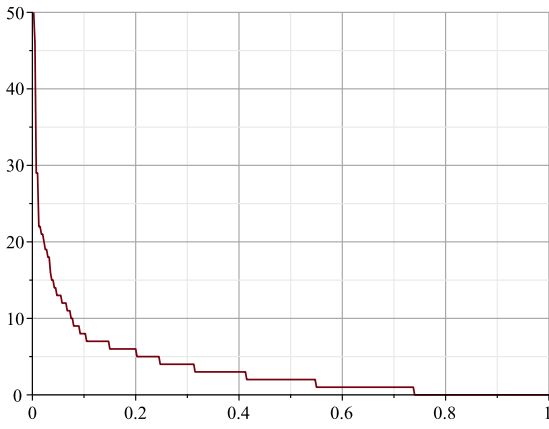


Fig. 7: Histogram of Pedestrian densities in Rome

C. Madrid

We have investigated Madrid in our analysis. There 3.2 million inhabitant in Madrid center. The data of Madrid [7] shows a total street length of 3,000 km, which is probably 6,000 km of pedestrian path. The pedestrian histogram (see figure ??, has been established over twelve independent random walks. It should be noted that street view shows more

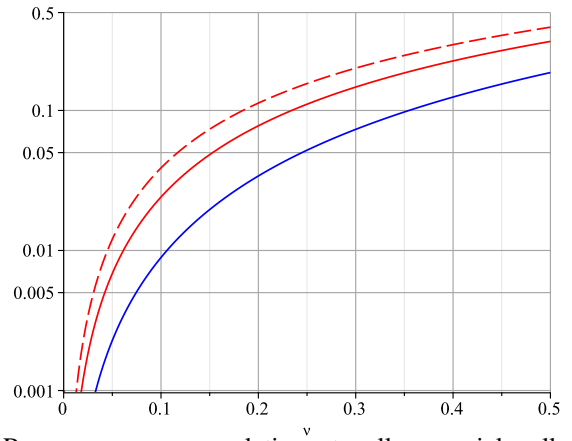


Fig. 8: Rome: exposure cumulative rate, all are social walkers but randomly dispatched on 10 hours (red), social walkers but concentrated on 5 hours (dashed red), all random walkers (blue) as function of the average outdoor excursion (in fraction of 10h)

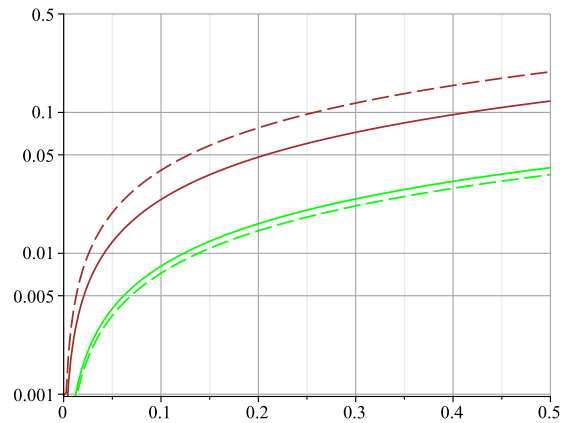


Fig. 9: Rome: exposure cumulative rate, in red, for a single walker in function of its excursion duration, when all other walkers are social walkers during 1 hour, in green when the single walker is random. In dashed when the social walkers select their slot on an interval of 5 hours

people in the streets than in the previous cities. And precisely there are more people in narrow streets than in wider streets, this would need a more careful study. The comparative effect of social and random walks are given in figure 11, figure 12 and table IV. It turns out that the reduction exposition factor is between 2.36 and 3.90 when all walkers are random walkers compared to the case when all walkers are social.

D. Paris under Zipf 1 hypothesis

As we stated in the beginning of our sampled histograms, we expect that the actual density distribution during lock-down is much steeper than before lock-down, since many areas have lost their natural attiring properties. In the following we investigate the hypothesis that the histogram is now of Zipf of coefficient 1, instead of coefficient around 0.75. The figure 13

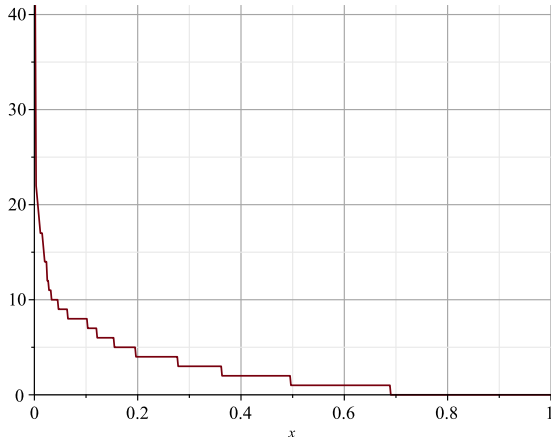


Fig. 10: Histogram of Pedestrian densities in Madrid

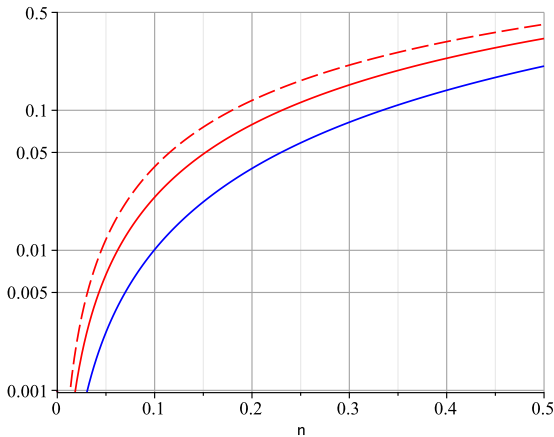


Fig. 11: Madrid: exposure cumulative rate, all are social walkers but randomly dispatched on 10 hours (red), social walkers but concentrated on 5 hours (dashed red), all random walkers (blue) as function of the average outdoor excursion (in fraction of 10h)

shows the theoretical histogram. It should be noticed that in this case 5% of the streets attract more than 50% of pedestrians (e.g. river banks, parks, spectacular avenues). The consequence on exposure rate versus random walks is even more strong, see figures 14 and 15, summarized in table V, where 1 hour of random walk give an exposure rate lower than 10mn social walk. Or conversely, to get the equivalent of 1 hour of social walk, the random walker could walk more than 6 hour in average.

It also turns out that the reduction exposition factor is between 3.70 and 4.41 when all walkers are random walkers compared to the case when all walkers are social.

E. Exposure reduction rate and other cities

In table VI we display the exposition rate ratio between all social walkers and all random walkers (all during one hour per day). Between parenthesis the exposition rate ratio when all social walkers are concentrated. These are the result of respectively formula $\frac{E_G(0.1)}{E_U(0.1)}$ and $\frac{E_G(0.2)}{E_U(0.1)}$. On the left column the social walkers walks according to pre-lockdown average

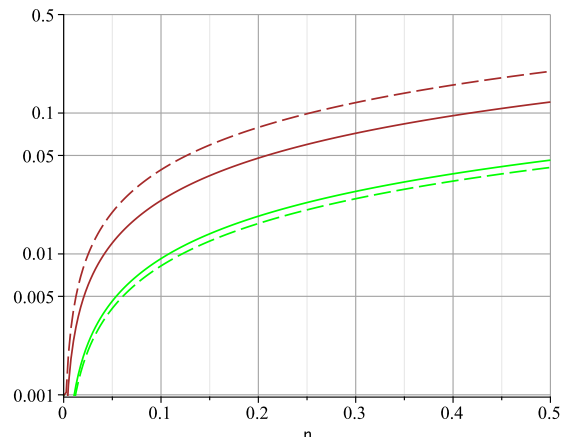


Fig. 12: Madrid: exposure cumulative rate, in red, for a single walker in function of its excursion duration, when all other walkers are social walkers during 1 hour, in green when the single walker is random. In dashed when the social walkers select their slot on an interval of 5 hours

columns: equivalent times	all social walkers	one variable social other 1 hour social	all random walkers	one variable random other 1 hour social
1 hour all social	1h (0h44mn)	1h (0h36mn)	1h34mn	2h15mn (2h57mn)
1 hour all random	37mn (27mn)	24mn (13mn)	1h	1h05mn (1h13mn)
1 hour random other social	35mn (25mn)	22mn (13mn)	57mn	1h (1h07mn)

TABLE IV: Madrid: per column, the equivalent exposure times for respectively 1 hour of all social walkers, of all random walkers, of one random walker, the other being social walkers. In parentheses when the social walkers are concentrated on 5 hours

densities. On the right column, social walkers densities are assumed of Zipf with parameter 1. For Marseille we have calculated 1100 km of pedestrian path from [8]. For Barcelona we have calculated 2580 km.

IV. CONCLUSION

We have introduced the Ariadne String application to fight Covid exposure during outdoor excursions. We have shown that even a basic random walk significantly reduces the exposure. In particular 1 hour of random walk provides an the exposure rate smaller than 20 mn of social walk. We have modeled the performance under the sampling of social walk in three different cities: Paris, Manhattan, Rome, providing similar results. We have extrapolated these result during lockdown under a steeper Zipf distribution of coefficient 1, with even more spectacular result. The application Ariadne Covid is simple to set up and could be made available in most cities in the World.

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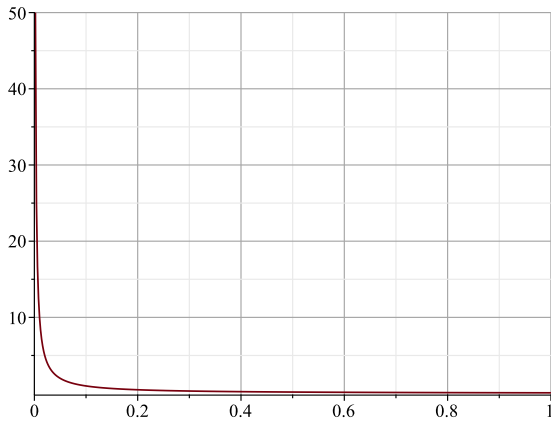


Fig. 13: Histogram of Pedestrian densities in Paris Zipf 1

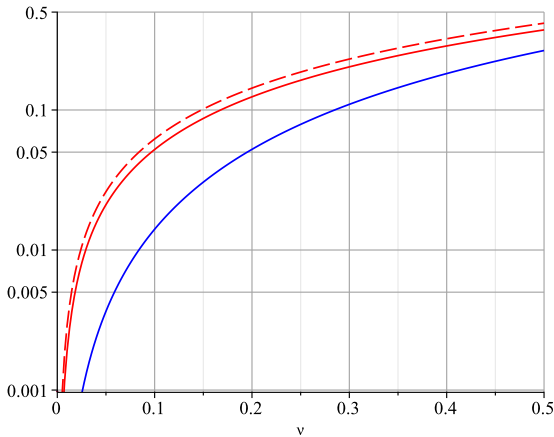


Fig. 14: Paris Zipf 1: exposure cumulative rate, all are social walkers but randomly dispatched on 10 hours (red), social walkers but concentrated on 5 hours (dashed red), all random walkers (blue) as function of the average outdoor excursion (in fraction of 10h)

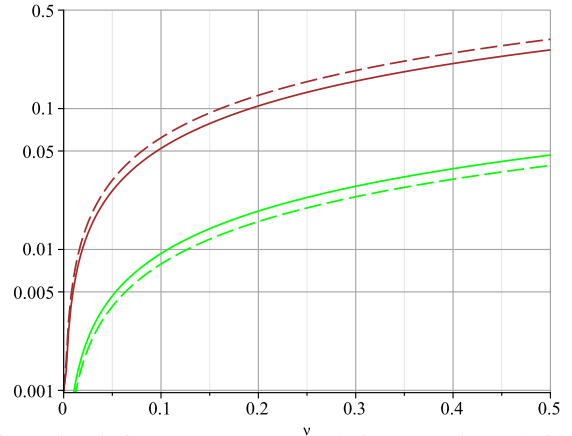


Fig. 15: Paris Zipf 1: exposure cumulative rate, in red, for a single walker in function of its excursion duration, when all other walkers are social walkers during 1 hour, in green when the single walker is random. In dashed when the social walkers select their slot on an interval of 5 hours

columns: equivalent times	all social walkers	one variable social other 1 hour social	all random walkers	one variable random other 1 hour social
1 hour all social	1h (0h52mn)	1h (0h50mn)	1h59mn	5h33mn (6h36mn)
1 hour all random	22mn (18mn)	16mn (13mn)	1h	1h30mn (1h47mn)
1 hour random other social	16mn (13mn)	10mn (09mn)	48mn	1h (1h11mn)

TABLE V: Paris Zipf 1: per column, the equivalent exposure times for respectively 1 hour of all social walkers, of all random walkers, of one random walker, the other being social walkers. In parentheses when the social walkers are concentrated on 5 hours

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Cities:	pre-lockdown data	Zipf 1 hypothesis
Paris	2.21 (3.45)	3.70 (4.41)
Manhattan	2.05 (3.10)	3.09 (3.63)
Rome	2.70 (4.35)	5.07 (6.19)
Madrid	3.70 (4.41)	4.65 (5.64)
Marseille	2.77 (4.31)	3.81 (4.54)
Barcelona	2.22 (3.57)	4.20 (5.04)

TABLE VI: Other cities: all random walker exposure reduction rate, versus all social, all social under Zipf 1, between parentheses: all social concentrated.