Bus, Bike and Random Journeys: Crowdsourcing Aid Distribution in Ivory Coast

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In many developing countries (e.g., Ivory Coast, Ghana, Liberia, Nigeria), half the population lives in rural locations, where accessibility to school materials, medical supplies, mosquito nets, and clothing is restricted [2]. Distribution to these locations typically requires direct road transport, which is time consuming and requires bulk volume to be cost effective. In response to these limitations, distributed methods of aid distribution have emerged in recent years. For example, Pack For a Purpose[1] is a non-profit organisation that asks tourists who already have a trip planned for one of 47 developing countries to bring small items (e.g., pencils, deflated soccer balls, stethoscopes) in their spare luggage capacity. Another scheme is Pelican Post[2], which asks donors to send books by post to developing countries. These are promising schemes. However, they fail during periods of conflict, (e.g., post-electoral violence in Ivory Coast in 2011) and are reliant on direct outsider support, when it is arguably preferable to empower local populations wherever possible.

Recently, we proposed a new distribution method that uses the natural mobility of a local population to distribute physical packages from one location to another [4]. In more detail, we considered the possibility of opportunistically using the pre-existing mobility routines of a set of local participants by asking them to pick up a package from one exchange point (at a location that they normally visit, at a time that they normally visit it) and then drop it off at another exchange point (e.g., a lockbox or affiliate store) that is also part of their regular mobility. By chaining together the mobility of several participants, we may cover a large area, possibly a whole country, without having to deploy more expensive and time consuming infrastructure.

For example, if we wish to deliver a package of mosquito nets from the capital, Abidjan, to a rural village in the west of Ivory Coast, we may first ask Ibrahim, who lives in Abidjan, but often visits his sister in Gagnoa (a city in the west) on Tuesdays, to pick up the package near his house and drop it off near his sister's house in Gagnoa, when he is there anyway. We may then ask another participant, Phillipe, who lives in Gagnoa, but who works in Taï national park on weekdays (driving past the village each day without realising) to drop the package off at the village on his way to work. In this way, the participants do not have to significantly change their schedules or travel long distances that they would not have otherwise travelled. The journey of the package in this example delivery is illustrated in Figure 1.

While potentially appealing, this vision of crowdsourced delivery faces significant technical barriers[3]. Specifically, how should we select the task assignments to minimise the length of time the delivery will take? Optimising routes is a recurring problem in computer science and a variety algorithms have been invented to do it efficiently, without requiring infeasible amounts of computation time and storage (e.g., Dijkstra's algorithm, A* search). The twist in crowdsourcing settings comes from the unavoidable fact that we are relying on humans to perform tasks, and we can never be really sure how they will behave. In package routing, we face uncertainty about *when* a participant will choose to travel to the next stage of the package's route. Fortunately, there exists a suite of tools in statistical machine learning and artificial intelligence that allow us to automatically make a robust set of sequential decisions that minimises the delivery delay under human location uncertainty. This is despite the fact that we only have messy and incomplete data about the participants' locations.

[1] `http://www.packforapurpose.org`

[2] `http://www.pelican-post.org`

[3] In addition to the social issues related to trust (e.g., theft or loss) and incentivisation that we briefly discuss at the end of this article.

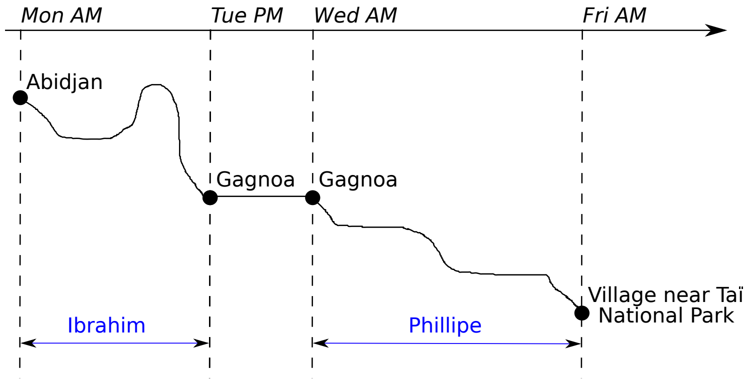

FIGURE 1: Example trajectory of a physical package across Ivory Coast using crowdsourcing.

Learning Mobility

The first component in our system is a probabilistic model of human location behaviour. It allows us to predict, given what we know about an individual's past locations, where is he or she expected to be at a given time in the future. It is probabilistic in the sense that each prediction is represented as a probability distribution over all possible locations, indicating how likely the individual is to be at that location for the given time (which sums to 1, of course, because the person must be *somewhere*, and they cannot be in more than one place at a time). Before deciding what form the model should take, we need to know what the data looks like. Most mobile phones in Africa do not have fine-grained global positioning system sensors (GPS), so we must make do with cell tower data, which is less precise. Cell tower data consists of a set of tuples (i, x_n, t_n) indicating that participant i was observed near cell tower x_n (discrete) at date and time t_n (continuous). There are three main factors that influence the design of the model:

1. **Cell allocation noise**
   The cell tower observations provide discrete measurements on the individual's likely location. However, there may be a choice of several towers that the phone can connect to (especially in urban environments) at any single location. This allocation is decided by outside factors that we treat as noise (i.e., the network operator's optimal allocation of phones to towers). Our approach needs to isolate the human presence information in the cell tower allocation to phones and ignore other factors. This implies the need to infer the locations, each of which may be statistically associated with several cell towers.

2. **Sporadic observations**
   Since the cell tower is only recorded in this dataset when a phone call or text is made (about 7 times a day, on average) we need a method that can fill in (extrapolate from other observations) large periods of no observability.

3. **Short duration**
   We are not guaranteed a long the history of data for all individuals. This, combined with the fact that each day may have only a few (or zero) observations, makes learning challenging. Overfitting is a danger when the training data (e.g., a few weeks of observations) contains characteristics that do not generalise to the rest of the individual's behaviour (i.e., beyond a few weeks).

These considerations suggest the use of the Bayesian framework, which allows us to assume the existence of latent variables that abstract away from the variability of cell allocation (Factor 1), and make custom assumptions about the smoothness of location (Factor 2). Furthermore, Bayesian non-parametric methods can provide us with powerful guards against overfitting (Factor 3).

In more detail, we assume the existence of latent discrete locations that are associated with each observation (i, x_n, t_n), and correspond to places in individual i's routine life (e.g., home, work). These locations are latent (i.e., hidden) in the sense that it is not possible to directly observe a person visiting them, but their existence is implied by the patterns of cell tower visits in space and time. For example, if there are two cell towers near my home, on some occasions my phone might be assigned to one, while on other occasions it might be assigned to the other. Although these assignments are random, over a long enough time we can make an educated guess about the existence of a single place of interest (i.e., my house) at that location. To do this, we can use mixture modelling to infer both the nature and number of latent locations from the data (using a Bayesian non-parametric approach called a *Dirichlet process*).

To address the problem of filling in large periods of missing data, we assume that behaviour is periodic. Specifically, we assume both weekly and daily periodicities in behaviour. In the model, we achieve this by decomposing the date/time observation t_n to the discrete day of the week and continuous hour of the day. The other motivation for using a periodic mobility model is that it allows predictions for arbitrary future time points, enabling optimisation to be done several days ahead (e.g., Tuesday at 2pm in 6 months' time).

Now that the model has been specified, it is possible to learn its parameters from any given set of observations. Once this is done, with the parameters in hand, we are free to disregard the observed data because everything we care to know about an individual's past behaviour is captured in those parameters.

But how do we know the model's predictions will be any good? This is an empirical question about the quality of our assumptions. George E. P. Box, an acclaimed English statistician who died earlier this year, once said "all models are wrong, but some are useful" [1]. One way of assessing the usefulness of our model is to check how much probability mass it assigns to future locations that were subsequently visited by the person. To do this, we used a dataset from the Orange phone network, describing the cell tower assignments of 50,000 individuals in Ivory Coast. We computed the parameters of all 50,000 individuals, but held back one observation per person to be used exclusively in testing the predictions (otherwise we would be testing with data that is, in some way, already represented by the parameters, making the reported performance artificially high). Comparing against the next best approach, we found that our model assigned 2.4 times as much probability mass to future locations on average.

So if we know that our predictions are pretty good, we now consider how we can use them to make optimal decisions about the package route and task assignments.

Optimisation

The optimisation problem is challenging because decisions made in the present affect what decisions can be made in the future. For example, sending the package to the west of the country limits the pool of participants to whom we can next assign tasks. A principled way of solving such sequential decision-making problems using existing methodologies exists in the form of the Markov decision process (MDP).

An MDP describes what happens when an agent (e.g., a person, robot, or piece of software) performs an action without knowing exactly what its effect will be. The uncertainty surrounding effects is represented by a probability distribution that describes the next state $s' \in S$ of the agent after it performs action $a \in A$ at current state $s \in S$. The exact interpretation of states (S) and actions (A) depends on the scenario being modelled. For example, the state of a robot on the surface of Mars could represent its position, while actions could represent the activation of various motors on the robot. In our case, the set of states represents the joint combination of delay and location in Ivory Coast (see Figure 2), while the set of actions represents the assignment of delivery tasks to participants.

One attractive feature of MDPs is that they come with a set of established methods (e.g., value iteration, policy iteration) for finding the optimal *policy* that specifies the best action to perform at any given state. Optimal in what respect? To answer this, we need to complete the specification of the MDP, as usual, by assigning a measure of desirability, or *utility*, to each state. In our scenario, the utility is simply the delay the package has experienced so far, though more elaborate representations of utility are certainly possible, (e.g., a quadratic

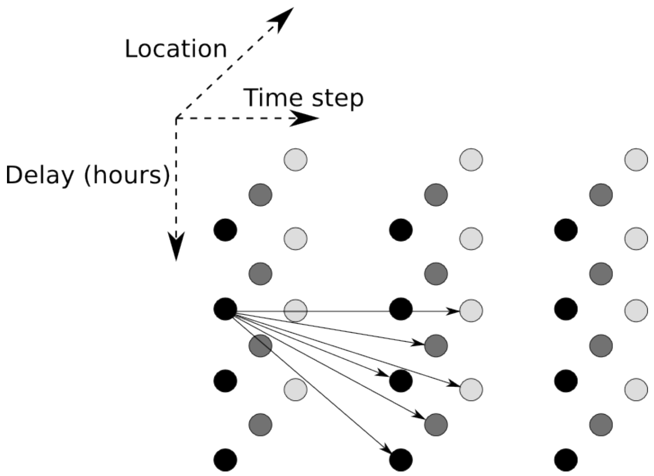

FIGURE 2: A subsample of the states of our MDP, illustrating the random transition after a single action. Each row represents a different delay, each column represents a different time step, and each shade of colour represents a different location.

function of delay that penalises higher delays much more than lower amounts of delay, or, a cost associated with involving a new person that represents the risk that they will lose or steal the package).

In theory, all we have to do is run policy iteration on our MDP and we will have the best task assignment for each state. But there is a catch. Consider again our representation of each state as the combination of a location and possible delay. A moment's thought will make clear that there is no limit to the amount of delay the package may experience. Delays of a week, a month, or even a year between steps in the route, though increasingly unlikely, are not ruled out by our mobility model or the scenario. This presents a major problem in searching the space of optimal decisions. This situation is fairly common for real-world problems: while it is easy to represent a scenario as an MDP, unless you have some clever formulation of states, you will often find it computationally infeasible to find an optimal policy in practice. Is such a formulation possible here?

To see how we might represent states more compactly, we need to go back to the mobility model. The function of interest is the probability density function $p(d_m|d_n, l_n, l_m, i)$ describing how long it will take participant i to bring the package from location l_n to location l_m, assuming that he was assigned the task d_n after the beginning of the package route. The periodic nature of the model means that this function is also periodic. This is a good thing, because it means there are only a limited number of values the function can take (assuming discrete delays of fixed time blocks, e.g., hours or half days). Formulated in this way, solving the MDP is now a tractable endeavour.

Putting everything together, the whole system for learning and optimisation is laid out in Figure 3. In learning, the mobility patterns of each individual are extracted. From this, it is possible to define the delay probability density function describing the transition probabilities in the MDP. Using the calculated optimal policy of the MDP, the next action (i.e., the participant to ask and the route the package should take) is decided by the package's current position.

Simulated Deliveries

Before rushing out to deploy our system in the real world, it makes sense to ask a few questions first. We want to check if anything about the mobility of the participants rules out the feasibility of crowdsourcing package delivery. To do this, we used data about the locations of real people (using the same Orange dataset as before) but simulate thousands of delivery problems to be solved with our framework. Our evaluation comprises four key criteria: (1) the number of participants required for acceptable geographical coverage; (2) the number of participants required in any specific delivery (since longer chains imply greater risk of loss and theft); (3) the feasibility of delivering to rural locations, which is expected to be much harder than urban delivery; and (4) the time required for each delivery.

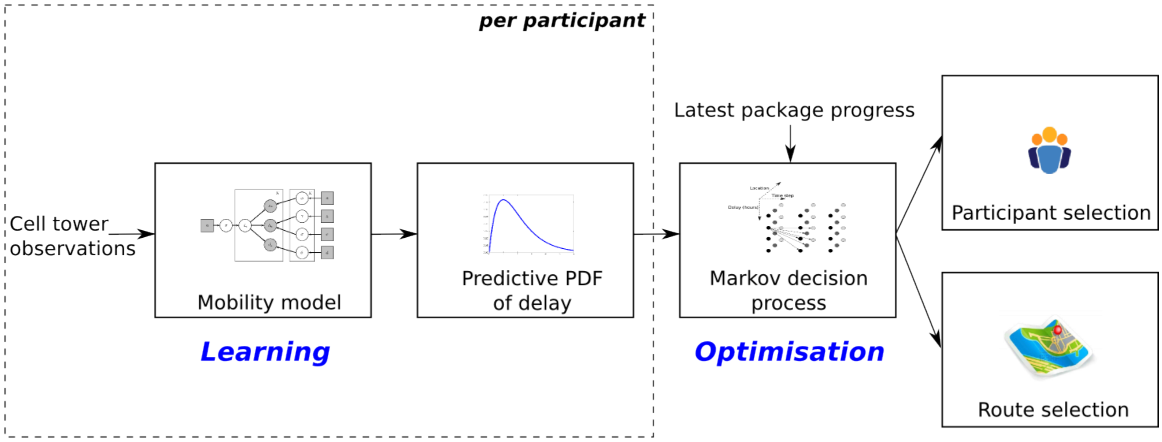

FIGURE 3: Complete crowdsourcing task assignment system for package delivery under human location uncertainty.

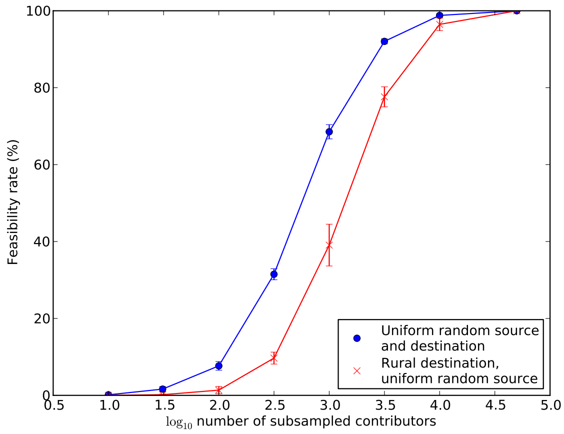

FIGURE 4: A plot of the percentage of randomly sampled (source,destination) delivery problems that had a solution path of any size, against the $\log_{10}$ size of the number of potential contributors.

Criterion 1: Number of Participants Required

Figure 4 shows the percentage of location pairs that were feasible (i.e., that had *any* path between the source and destination locations). The line with circular points shows the feasibility for uniform random source and destination locations. We see that the geographical coverage is very poor when there are fewer than $10^{2.5}$ participants. The critical range is around 10^3, when feasibility surges with each new participant. The heavy tail in human location behaviour is one explanation for this effect, where individuals visit many locations a few times (and a few locations many times) in their daily life mobility [3]. Therefore, an acceptable geographic coverage, trading off against recruitment/administration costs, appears to be around $10^{3.5}$ participants.

Criterion 2: Number of Participants Required for Any Given Delivery Problem

Figure 5 shows the number of participants required for the simulated delivery problems we considered. Since infeasible paths cannot be included when plotting (because they have unspecified numbers of contributors), the number of contributors required for specific paths initially increases with the size of the participant subset, as more paths are made feasible. However, once path feasibility (indicated in Figure 4) goes beyond 20%, the trend is as expected; having a wider pool of participants allows more efficient (i.e., shorter length) paths to be discovered.

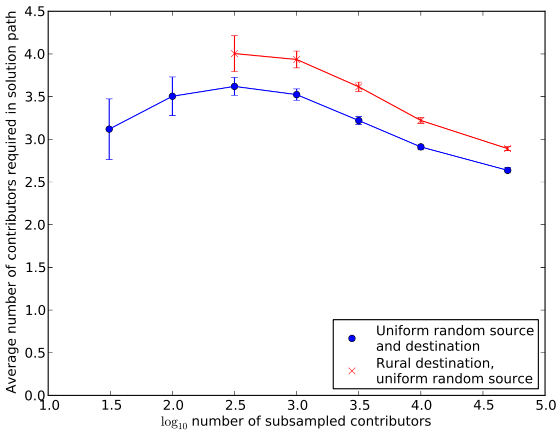

FIGURE 5: A plot of the average number of contributors required to each specific delivery problem (drawn from the much larger pool of potential contributors) against the $\log_{10}$ size of the potential contributors pool. N.B., a majority of rural destinations are infeasible for pool sizes of less than $10^{2.5}$, therefore we are unable to plot the line below this range.

Criterion 3: Rural Distribution

So far, we have only considered uniformly sampled source and destination test points, which favours urban locations (since there are greater numbers of cell towers in urban areas). We now consider Criterion 3 for rural feasibility, by sampling a set of delivery problems where the destinations are only rural (keeping source locations uniformly sampled, as before). We ran the same analyses for Criteria 1 and 2 with rural destinations, yielding the lines with crosses in Figures 4 and 5. This indicates that restricting the destinations to be rural certainly makes the delivery problem more challenging, but it is still feasible. Now that we know that all three feasibility criteria are met, we consider the problem of learning the temporal structure in mobility to enable the minimisation of delay in delivery from source to destination nodes.

Criterion 4: Time Required

To estimate the time it would take to make deliveries, we considered the hardest instantiation of our problem. If the delays for this hardest scenario are acceptable, then that is encouraging news. Firstly, we considered deliveries to only rural destinations, as delivery is much less of a problem in urban areas. Secondly, given the fact that any recruitment campaign would cost time and money, we considered a small participant pool of 3,500 (the smallest number of potential participants we could use while still keeping 80% of feasible routes, according to Figure 5). Under these conditions, the average time required for delivery was 30.0 days, which is 81.3% faster than using the naïve method of finding the route with the least number of contributors (which took 161 days, on average). So we get a big improvement from learning and optimising, though you would not want to send anything urgently in this manner (at least to rural destinations with a small number of participants). Given the low cost of using mobility opportunistically, perhaps a new model of delivery may emerge in which items can be sent continuously, much like the network of blood vessels in the body, as opposed to sending a bulk delivery of items using conventional truck delivery.

But Can It Really Work?

What other factors could stop our solution working in practice? To perform routing under uncertainty, we assumed that the participants would follow their normal mobility patterns when delivering packages. Clearly, additional factors could introduce further delay, including disruptions to transport and short term disruptions arising from participants' circumstances (e.g., being too busy, taking sick leave). In practical terms, most of the impact of these disruptions could be absorbed by an appropriate task assignment procedure. Specifically, after obtaining a policy from our learning and optimisation approach, the system could ask the selected participants, via automated phone text, whether they are actually willing and able to do the task. In this way, participants facing disruptions can be filtered out, limiting the introduction of unexpected delay into the route. On the other hand, some disruptions may not be known at the time of task acceptance, or some participants may simply not be honest about them. Investigating how to update an existing optimal policy with updated predictions, and how people respond to incentives in this scenario are therefore important questions for future research.

Finally, in the worst case (from a routing perspective), participants may lose or steal packages. A certain amount of loss and theft is assumed even with standard delivery, and is borne as the risk of doing business, or addressed with insurance. In the crowdsourced setting, this can be taken into account by assigning a cost to each participant (either with a fixed value, or derived from a participant-specific trust evaluation framework). In whatever way the cost of trust is calculated, once obtained, it can be incorporated into the MDP as an added cost in the standard way.

It remains to be confirmed how crucial these issues would prove in practice. If they are not crucial, or if they can be mitigated along the lines we provided, then our system has promise in being cheaper and greener than the conventional alternatives of package delivery. Furthermore, in altruistic applications like development of poorer countires, getting more citizens involved has the potential to create a more cooperative and inclusive society. This scenario is only one idea in the much larger ORCHID project (`orchid.ac.uk`), which aims to establish the new science of human-agent interaction. As people and agents form cooperative groups, or collectives, it is important to address the types of challenges we saw here (though we only addressed the first), such as processing uncertain human behaviour, designing incentives, and dealing with the trustworthiness of participants. The benefit to society is the ability to get more value from the contributions of humans and agents in domains as diverse as citizen science, disaster response, and energy management systems.

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