The Impact of Environmental Stressors on Human Trafficking

Sabina Tomkins*, Golnoosh Farnadi*, Brian Amanatullah†, Lise Getoor* and Steven Minton†
UC Santa Cruz*, InferLink†
Email: *{satomkin,gfarnadi,getoor}@ucsc.edu, †{bamanatullah,sminton}@inferlink.com,

***Abstract*—Severe environmental events have extreme effects on all segments of society, including criminal activity. Extreme weather events, such as tropical storms, fires, and floods create instability in communities, and can be exploited by criminal organizations. Here we investigate the potential impact of catastrophic storms on the criminal activity of human trafficking. We propose three theories of how these catastrophic storms might impact trafficking and provide evidence for each. Researching human trafficking is made difficult by its illicit nature and the obscurity of high-quality data. Here, we analyze online advertisements for services which can be collected at scale and provide insights into traffickers' behavior. To successfully combine relevant heterogenous sources of information, as well as spatial and temporal structure, we propose a collective, probabilistic approach. We implement this approach with Probabilistic Soft Logic, a probabilistic programming framework which can flexibly model relational structure and for which inference of future locations is highly efficient. Furthermore, this framework can be used to model hidden structure, such as latent links between locations. Our proposed approach can model *and* predict how traffickers move. In addition, we propose a model which learns connections between locations. This model is then adapted to have knowledge of environmental events, and we demonstrate that incorporating knowledge of environmental events can improve prediction of future locations. While we have validated our models on the impact of severe weather on human trafficking, we believe our models can be generalized to a variety of other settings in which environmental events impact human behavior.**

I. Introduction

Global temperatures are projected to rise an estimated 8-11°F over the course of the next century [1]. This overall temperature increase will be accompanied by changing climates, resulting in extreme weather and changes to stable ecosystems. While climate change is a serious environmental threat, it also poses significant risks to human well-being and social systems [2], [3]. One projected impact of climate change is on security outcomes, altering and potentially increasing opportunities for crime [4], [5].

Understanding the relationship between environmental stressors and criminal activity requires utilizing multiple heterogenous data, from both online and offline sources. We propose to model the relationship between environmental stressors and crime though a probabilistic approach which can fuse multiple heterogenous signals and model spatial and temporal relationships. We evaluate the feasibility of this approach by analyzing the relationship between extreme weather events and human trafficking.

An estimated 20.9 million people are victims of human trafficking [6]. Of these, an estimated 2 million are children. Any efforts towards the reduction of trafficking have the potential to drastically improve the quality of life of victims.

Studying the dynamics of human trafficking, from victim characteristics to risk factors, is complicated by the difficulty of acquiring reliable data on a population which strives to avoid detection [7]–[9]. Victims face many barriers to sharing information with law enforcement, from repercussions from abusers, to lack of access to and mistrust of law enforcement. Typical sources of information are victims' testimonies from non-governmental organizations and printed materials.

Alternatively, there is a wealth of information available from online sources. Human traffickers post advertisements for sexual services on public websites, such as Backpage.com. Thus, it is possible to collect large amounts of advertisements where the service provider may be a victim of trafficking. However, traffickers take care to obfuscate identifiable features, such as phone numbers, and advanced tools are needed to extract relevant information. Knowledge graphs are one tool which have proven successful at capturing relevant details from online advertisements [10]. These extracted entities, such as physical characteristics of potential victims, can be used to better study trafficking [11], [12]. For example, when it is possible to extract them, the phone numbers from ads can be used to reconstruct trafficking routes or circuits [13].

We have collected online advertisements posted on websites where traffickers advertise the services of their victims. By applying entity extraction techniques to these ads, we can extract relevant information such as: phone numbers, location information, and details on the demographics of the service providers. Using the phone numbers which identify ad posters and the locations of ads, we can track the movements of ad-posters over time. For the remainder of the paper we use the term trafficker to refer to these ad-posters.

In our work, we combine online data with offline knowledge of extreme weather events. We investigate the open question of how extreme weather events might impact trafficking. Deepening our understanding of this relationship can assist efforts in apprehending traffickers, especially in the aftermath of such events. Furthermore, our approach can be generalized to a variety of other situations in which environmental stressors impact security outcomes.

As a preliminary study of this complex relationship, we propose three potential effects of catastrophic storms on human trafficking: change in vulnerability of effected populations, change in attraction of effected areas and change in trafficking routes. We summarize these potential effects with the following research questions:

- R1: Is there a measurable change in the vulnerability of effected populations?
- R2: After an extreme event, how does the volume of trafficking change in effected areas?
- R3: Do extreme events disrupt trafficking routes?

We investigate two environmental events: *Hurricane Matthew* and *Typhoon Goni*. Hurricane Matthew inflicted heavy damages throughout the Caribbean and southeastern United States. Here, we have the opportunity to inspect the diverse effects of a wide-ranging natural disaster. Typhoon Goni affected many in East Asia. By studying these two environmental events, we can compare their effect on human trafficking across the globe.

We propose a series of three probabilistic spatio-temporal models to predict traffickers' movements. The first model predicts where traffickers will go next without any knowledge of extreme events. We demonstrate that this simple model achieves a reasonable F-Measure at predicting future locations.

Additionally, we propose a model which infers structure between locations as route segments. Such a model can capture longer-term dependencies between movements. For example, knowing where an ad-poster was two time-steps ago may help differentiate between two otherwise ambiguous future locations. This model also predicts movements while allowing us to learn which locations are linked. By incorporating spatial structure, we can augment cases where evidence of travel is lacking. We extend this model with an event-aware model which predicts where traffickers will go in the aftermath of an extreme event. We implement our models in Probabilistic Soft Logic (PSL) [14], a probabilistic programming framework in which we can model this task's spatio-temporal structure.

We present a novel analysis of how environmental events effect human trafficking. Before addressing this relationship we introduce some background on human trafficking in Section II. We then address R1 and R2 in Section III. In Section IV we introduce our probabilistic models and in Section V we evaluate their ability to predict future locations and to discover route segments while addressing R3.

II. Sources, Destinations, and Transit Hubs

Nations with human trafficking activity can be categorized as sources, destinations, transit hubs or some combination thereof [15]. Source countries are countries of origin for victims of trafficking. Destination countries are those where victims are taken. Transit countries are those which victims pass through. These distinctions hold ramifications for how traffickers travel within, to and from various countries.

In our data we investigate trafficking primarily in two countries: the United States and the Philippines. The United States is both a source, a destination and a transit country [16]. Furthermore, it is the second largest destination country in the world [17] and understanding trafficking behavior in the United States has global ramifications. The Philippines is primarily a source country, although it also has destination locations, and serves as a transit hub [16]. Furthermore, the Philippines is one of the top three source destinations for victims in the United States [16] . As the largest number of female and children victims are trafficked either within Asia, or are from Asian countries [18] and an estimated 3% of the Philippine population is at risk of being trafficked at any time [19], this is an important area to study. These characteristics that differentiate source and destination countries might influence how environmental events effect trafficking in each.

III. Impacts on Trafficking

In this section we address research questions one and two. First, we begin with a description of the data. To produce the results of this study, we analyzed a dataset collected over several years from websites with prostitution-related ads and/or reviews. The ads in this dataset include many noisy attributes, including the city the ad was posted in, phone numbers, and personal attributes such as ethnicity, weight, eye color, etc.

A multi-phase process was used to collect this data. Web pages on the sites were retrieved by crawling the sites on a regular basis. To extract the data in ads on the site, two types of extraction techniques were utilized. The first technique identifies semi-structured data on the site, that is, data that is displayed on the site in a template-style structure. Most commercial web sites that post ads for sex providers have such a template structure, so that data items such as phone numbers, prices, and physical attributes of the victim are displayed in the same place on each advertisement page. Our extraction software automatically identifies this type of template structure on a site through the use of a machine learning approach. This approach first clusters the pages based on the overall similarity of the pages, so that (ideally) each cluster has a single type of template on the page. Then, each cluster of pages is analyzed more carefully to identify a grammar that describes the template used on those pages, allowing the system to automatically extract the data fields from the template. Finally, a human user curates the data the first time the site is processed, in order to confirm the labels provided by the system, and then the process operates automatically on subsequent crawls. Because some of the data fields in the templates often contain free text (such as a free text description of the service provider's "expertise"), we also use a second technique to extract data. In particular, we use site-independent extraction rules to look for specific types of data, such as ethnicities (e.g., Asian, Swedish) that have a distinctive vocabulary, as well as fields that have a distinctive internal structure (such as phone numbers). Used together, these two techniques provide higher recall than if a single technique is used alone.

Figure 1 shows a real online ad. As is typical, the ad describes physical characteristics such as ethnicity. Also to note is the term 'visiting', and the short time span of the visit. This ad includes a phone number which can be extracted to track movements, though it has been blacked out here.

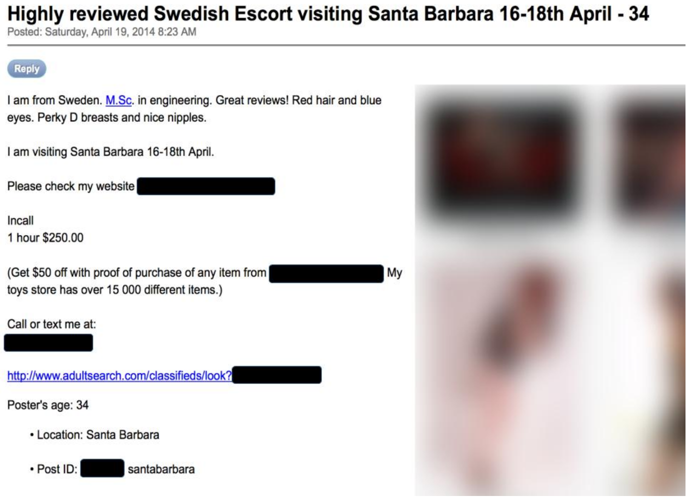

Fig. 1: Sample online ad.

A. Vulnerability Assessment

Environmental events can expose populations to risk, forcing people to lose their homes and their livelihoods. The Polaris report [20] identified recent migration or relocation as the top risk factor for rescued victims of human trafficking. Vulnerable populations may then become targets for traffickers in a number of ways. For example, seeking new opportunities, victims of natural disasters may put trust in traffickers who claim to be offering well-paying jobs. Additionally, as law enforcement divert resources to rescue and repair, it may be easier for traffickers to abduct victims. The end result of this increased vulnerability may be that we see increases in postings which advertise ethnicities associated with a vulnerable population. Alternatively, environmental stressors may increase the difficulty of traveling to effected areas, and we may observe a decreases in the vulnerability of effected populations.

In assessing vulnerability we consider two events: Hurricane Matthew and Typhoon Goni. Matthew was a category 5 hurricane, which struck the Carribbean and the southeastern United States in October 2016. This hurricane resulted in 603 fatalities and an estimated 15.09 billion in damages. Typhoon Goni was a large tropical storm which struck much of East Asia in August 2015. Goni resulted in 74 confirmed deaths and an estimated 831.7 million in damages.

To quantify changes in vulnerability of affected populations, we inspect the ad mentions of ethnicities from effected areas. To control for annual fluctuations in the total number of posted ads, we consider relative changes in the percentage of ads mentioning a given ethnicity. In doing so, we also need to control for seasonal patterns which can influence the ad volume at specific times of the year. To do so we take the following approach: for the year of a hurricane we calculate the change in ad volume between the month preceding and the month following a hurricane. We also calculate this ratio in the year before the hurricane. Let relative ad volume RAV(time, ethnicity) be a function which returns the percentage of ads posted in a period of time which mention a given ethnicity, e, and let m_i^j be a time period of month i during year j. We then define,

$$\delta_h = \frac{RAV(m_{i+1}^j, e)}{RAV(m_i^j, e)}, \quad \delta_p = \frac{RAV(m_{i+1}^{j-1}, e)}{RAV(m_i^{j-1}), e},$$
$$d_h = \frac{RAV(m_{i+1}^j, e) - RAV(m_i^j, e)}{RAV(m_i^j, e)}.$$

Thus δ_h and δ_p capture the change in volume between two periods, where δ_h refers to the year of the hurricane and δ_p refers to the previous year. By comparing these two measures we can determine if a greater change occurred in the year of the hurricane or the previous year. We also look at the difference in subsequent periods with d_h.

Hurricane Matthew: Matthew had a devastating effect on the Caribbean, and consequently, we inspect whether Caribbean populations experienced an increased vulnerability to human trafficking. To measure changes in vulnerability, we inspect the relative number of ads mentioning Caribbean ethnicities. In Fig. 2, we present d_h for the time period of Hurricane Matthew. We show only those cities where the difference between δ_h and δ_p was statistically significant according to a chi-squared contingency test. We see that several Florida cities witnessed statistically significant increases in ads mentioning Caribbean ethnicities. The largest increase is seen in Jacksonville. We observe statistically significant increases in mentions of Jamaican ethnicities in Jacksonville (of 160%).

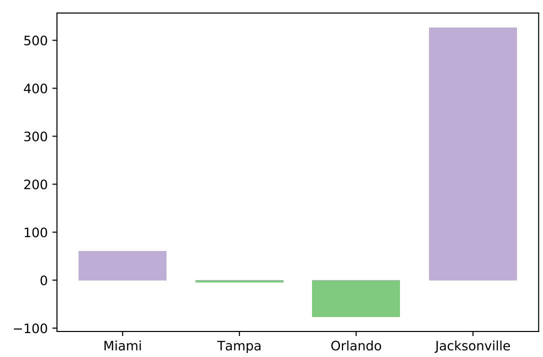

Fig. 2: The relative percent change in ad mentions d_h for Caribbean ethnicity for cities in Florida after Hurricane Matthew.

Typhoon Goni: Additionally, we consider a different kind of environmental event in a different part of the world. Here we investigate the impact of Typhoon Goni. Goni had a large impact on the Philippines, and we inspect whether any locations saw an increase in postings mentioning Philippine ethnicities. We found that two locations had statistically significant increases: Dubai (United Arab Emirates) and New York (United States). Dubai's increase by far dwarfed that of New York at 249% to .9%. Additionally, the majority of these postings were made with new phone numbers: 90% new numbers in Dubai and 28% in New York. Historically, roughly 14% of postings are listed with new phone numbers. This supports the theory that new victims of 'filipino' descent were advertised in these locations after Goni, lending credence to the hypothesis that these victims were only recently trafficked after the typhoon.

B. Trafficker Movements

Next, we ask if environmental stressors force traffickers to leave or enter affected areas. To do so, we consider the phone numbers which are included in posted advertisements. It is not always possible to successfully extract phone numbers from ads, and not all ads include them in the first place. Thus, these findings represent a sample of what might be found with full phone number data. We first focus this analysis on the United States. In the state of Florida we inspect all locations where the ads on the day of the hurricane are a small fraction of the historical average. Doing so, we find that the locations with the smallest ad fractions are on the Eastern coast of Florida in the projected path of Hurricane Matthew.

Location	Ads on Day of Hurricane	Following Week Daily Average	Historical Average
Jacksonville	25	187	193 $\pm$12
West Palm Beach	82	171	267 $\pm$20

TABLE I: Ad activity for affected Florida cities before and after Hurricane Mathew. The historical average also shows the standard error of the mean.

We first assess the possibility of traffickers leaving affected areas. In this analysis, we inspect how many phone numbers posted in the week before each event remain in the following week. In Jacksonville, we see an average of 149 ads/day in the week preceding the hurricane. On the day of the hurricane this drops to 25. Of the numbers posted in the week preceding, 66.3% are missing in the next week (compared to a national historical average of 22%). In West Palm Beach, 56% of numbers are missing in the following week. Thus, we do see that the hurricane forces an abnormally large number of traffickers to decrease their posting activity. That the majority of phone numbers in the next week are new to the area might indicate that traffickers leave environmentally effected areas.

Alternatively, after the immediate chaos of the event, traffickers might increase their activity in affected areas. An increase in trafficking could be attributed to a decreased risk of detection, as law enforcement diverts attention to rescue and repair. To investigate this, we look at the number of ads from three days after the hurricane to ten days. As we see decreased activity in the days immediately following the hurricane, by considering the activity from three days after we can isolate some of the incoming from the outgoing traffic. However, we continue to see depleted numbers in the following week in West Palm Beach, while Jacksonville sees maintained levels.

In the Philippines we observe a different trend. Here, in the effected area of Santa Ana, we see increases in ads in the timeframe of the hurricane. On August 22nd, 2015, we see 125 ads posted in Santa Ana. This compares to a historical average of 43 ($\pm$3.5) ads per day. There are many possible explanations for this increase which deserve exploring. For example, one explanation is that traffickers are drawn to an area with reduced law enforcement. Another explanation is that Santa Ana may be relatively more stable than surrounding areas. In this data we do not have comprehensive postings for the entirety of the Philippines, and locations with small postings are left out. However, given postings of more municipalities, we may learn more about how the effects of environmental events can vary by population and centrality to the event.

Together, both the influx and outflux of traffickers hold important insights for law enforcement. Traffickers may leave affected areas, disrupting any current plans for apprehension. Simultaneously, or with some small delay, new groups of traffickers may enter the same area. Thus any effort to apprehend previous traffickers, such as gathered intelligence, may not apply to these new groups.

IV. Spatio-Temporal Models

In order to model trafficking routes, we propose three spatial probabilistic models which predict the movements of traffickers. The first model utilizes spatio-temporal relationships and location ad characteristics to predict where traffickers will go next. The second model employs latent-variables to more explicitly model transit relationships between locations by identifying *route-segments*. This latent formulation allows for additional modeling capabilities of how ad-posters move. Furthermore, the discovered values for latent route-segments variables can be used to better understand spatio-temporal dynamics of trafficking. Finally, we introduce an event-aware route-segment discovery model. This model utilizes knowledge of external events to also predict locations and discover route-segments.

We implement these models using Probabilistic Soft Logic (PSL) [14], a probabilistic programming framework which allows for flexible modeling of temporal and spatial dependencies between both observed and unobserved random variables. In PSL, these dependencies are encoded with weighted logical rules which are translated into a graphical model. Crucially, the weights to these rules are learned through data and do not need to be specified a priori.

To illustrate PSL in the human-trafficking context, consider a rule which says that if two locations are geographically close, traffickers are likely to move between them. To express this rule, we introduce the predicate NEIGHBORS, which takes two locations as arguments and which expresses their spatial closeness as a value between 0 and 1. Additionally, we introduce the predicates LOCATION and NEXTLOCATION which both take a phone number id $PNumID$, a time, t, and a location id l, as arguments, and whose truth value indicates whether $PNumID$ is at l at time t. Together a predicate and its arguments form a logical atom; unlike in Boolean logic, PSL atoms can assume soft truth values in $[0, 1]$. With these predicates, and a weight w_{move} which reflects the relative importance of this rule, we define our rule in PSL as follows:

1. $w_{l_i l_j}$: $\textsc{Location}(PNumID, t_k, l_i) \wedge \textsc{Precedes}(t_k, t_{k+1}) \Rightarrow \textsc{NextLocation}(PNumID, t_{k+1}, l_j)$
2. w_v : $\textsc{Location}(PNumID, t_k, l_i) \wedge \textsc{Precedes}(t_k, t_{k+1}) \wedge \textsc{CloseGreatCircle}(l_i, l_j) \Rightarrow \textsc{NextLocation}(PNumID, t_{k+1}, l_j)$
3. w_s : $\textsc{Location}(PNumID, t_k, l_i) \wedge \textsc{Precedes}(t_k, t_{k+1}) \wedge \textsc{SameState}(l_i, l_j) \Rightarrow \textsc{NextLocation}(PNumID, t_{k+1}, l_j)$
4. w_c : $\textsc{Location}(PNumID, t_k, l_i) \wedge \textsc{Precedes}(t_k, t_{k+1}) \wedge \textsc{SimCity}(l_i, l_j) \Rightarrow \textsc{NextLocation}(PNumID, t_{k+1}, l_j)$
5. ∞ : $\sum_{l \in Locations} \textsc{NextLocation}(PNumID, T, l) = 1$

TABLE II: Rules for the model SPATIO-TEMPORAL.

$$w_{move} : \textsc{Location}(PNumID, t, l_i) \wedge \textsc{Neighbors}(l_i, l_j) \Rightarrow \textsc{NextLocation}(PNumID, t+1, l_j).$$

Combined with data, a PSL model defines a joint probability distribution over locations. This distribution is expressed with a *hinge-loss* Markov random field (HL-MRF) [14], a general class of conditional, continuous probabilistic graphical models. Formally, a HL-MRF describes the following probability density function over vectors of observed, $\boldsymbol{x}$, and unobserved, $\boldsymbol{y}$, continuous random variables:

$$P(\boldsymbol{y}|\boldsymbol{x}) \propto exp\left(-\sum_{j=1}^{m} w_j \phi_j(\boldsymbol{y}, \boldsymbol{x})\right)$$

ϕ_j is a *hinge-loss* potential, $\phi_j = \max\{l_j(\boldsymbol{x}, \boldsymbol{y}), 0\}^p, p \in \{1, 2\}$, l_j is a linear function of $\boldsymbol{x}$ and $\boldsymbol{y}$ and w_j is the positive weight associated with ϕ_j.

The logical rules defined in a PSL model translate to the weighted potentials ϕ, where atoms represent either observed ($\boldsymbol{x}$) or unobserved random variables ($\boldsymbol{y}$). As maximum a posteriori (MAP) inference in a HL-MRF can be formulated as a convex problem, we can tractably and efficiently infer the values to $\boldsymbol{y}$ with the PSL software[1]. The optimization technique is based upon the alternating direction method of multipliers ADMM [21].

We propose three models which use PSL to template spatio-temporal relationships and apply these relationships towards predicting the locations of human traffickers. The first model uses spatio-temporal rules to predict traffickers' locations, and the next models use event-information to improve these predictions. The second model expands on the spatio-temporal model to simultaneously discover routes while predicting future movements. Finally, we expand this *route segment discovery* model to make predictions with awareness of environmental events. In each model, the target variable is the next location l of each trafficker, $PNumID$, at time T_{k+1}, denoted $\textsc{NextLocation}(PNumID, T_{k+1}, l)$.

A. Location Prediction Model

In this first model, which we refer to as SPATIO-TEMPORAL, we predict future movements using spatial relationships, movement patterns between locations, and demographic similarities between locations. We model the tendency to move from each location to any other with rule 1 in Table II. This rule introduces $Precedes(t_k, t_{k+1})$, which is 1 if timestamp t_k immediately precedes timestamp t_{k+1} in a series of time-indexed locations. By learning a different weight w_{l_i,l_j} for each location pair, i, j, we can learn the relative frequency with which traffickers move from each location to the next. In rules 2 and 3 in Table II, we express that traffickers are likely to move between locations which are spatially close. Here we use two distance measures. One is the great-circle distance[2], where $\textsc{CloseGreatCircle}(l_i, l_j)$ expresses the geographic closeness of two locations, the other is a boolean value of whether two locations are in the same state, $\textsc{SameState}(l_i, l_j)$.

In addition, we introduce a measure of ad similarities between two cities. Such a measure can supplement missing data when traffickers abruptly delete phone numbers and/or acquire new phones. For example, if we know that two cities have highly similar ads it may suggest that they are visited by the same traffickers. As one measure of the similarity of ads, we consider similarities in the distributions of mentioned ethnicities. We model these location distribution similarities with $\textsc{SimCity}(l_i, l_j)$. Rule 4 expresses that a trafficker might next visit a location with an ethnicity distribution similar to that of their current location.

The final rule in Table II is a hard constraint. Hard constraints relate the truth values of given variables. For example, if there is certainty that a given trafficker is in a certain location at a given time, they cannot also be at another location at the same time. To express that a constraint must be satisfied it is given infinite weight.

B. Route Segment Discovery Model

In addition to predicting future movements of traffickers, we infer connected route components, which we refer to as route segments. These segments can be links between pairs of cities which are frequently traveled between, or longer paths of destinations which are visited in a sequence. To model these dynamics, we introduce the model ROUTE-SEGMENTS. We model route segments with a set of latent variables which describe their behavior. To describe if a location is on a route segment, we introduce $\textsc{OnRouteSg}(L, RS)$ and to describe that traffickers move from location l_1 to location l_2, we introduce $\textsc{Link}(l_1, l_2)$. A LINK expresses a directed relationships and is also a latent variable whose value we

[1] http://psl.linqs.org

[2] https://en.wikipedia.org/wiki/Great-circle_distance

1. $w_{npr} : \neg\textsc{OnRouteSg}(X, RS)$
2. $w_{npl} : \neg\textsc{Link}(X, Y)$
3. $w_{plr} : \textsc{LocationID}(X) \wedge \textsc{RouteSgID}(RS) \Rightarrow \textsc{OnRouteSg}(X, RS)$
4. $w_{ltr} :$ $\textsc{Location}$(PNumID,T,X) $\wedge\ \textsc{OnRouteSg}(X, RS) \Rightarrow \textsc{RLocation}(PNumID, X, R, T)$
5. $w_{rp} : \textsc{RLocation}(PNumID, X, RS, T) \Rightarrow \textsc{OnRouteSg}(X, RS)$
6. $w_v : \textsc{CloseGreatCircle}(X, Y) \wedge \textsc{OnRouteSg}(X, RS) \wedge \textsc{OnRouteSg}(Y, RS) \Rightarrow \textsc{Links}(X, Y)$
7. $w_s : \textsc{SameState}(X, Y) \wedge \textsc{OnRouteSg}(X, RS) \wedge \textsc{OnRouteSg}(Y, RS) \Rightarrow \textsc{Links}(X, Y)$
8. $w_{rc} : \textsc{OnRouteSg}(X, RS) \wedge \textsc{OnRouteSg}(Y, RS) \wedge \textsc{Precedes}(T_1, T_2) \wedge \textsc{Location}(PNumID, T_1, X)$
   $\wedge\ \textsc{Location}(PNumID, T_2, Y) \Rightarrow \textsc{Links}(X, Y)$
9. $w_{sc} : \textsc{SimCity}(X, Y) \Rightarrow \textsc{Links}(X, Y)$
10. $w_{rl} : \textsc{OnRouteSg}(Y, RS) \wedge \textsc{Links}(X, Y) \Rightarrow \textsc{OnRouteSg}(Y, RS)$
11. $w_{l_1 l_2} : \textsc{RLocation}(PNumID, X, RS, T_1) \wedge \textsc{Precedes}(T_1, T_2) \Rightarrow \textsc{NextLocation}(PNumID, T_2, Y)$
12. $\infty : \sum_{l \in Locations} \textsc{NextLocation}(PNumID, T, l) = 1$
13. $\infty : \sum_{l \in Locations} \textsc{RLocation}(PNumID, T, RS, l) = 1$
14. $w_{ef} : \textsc{RLocation}(PNumID, X, RS, T_1) \wedge \textsc{Effected}(Y) \wedge \textsc{Links}(Y, Z) \wedge \textsc{PostEvent}(T) \wedge \textsc{Precedes}(T_1, T_2)$
    $\Rightarrow \textsc{NextLocation}(PNumID, T_2, Z)$
15. $w_{eb} : \textsc{RLocation}(PNumIDX, RS, T_1) \wedge \textsc{Effected}(Y) \wedge \textsc{Links}(Z, X) \wedge \textsc{PostEvent}(T) \wedge \textsc{Precedes}(T_1, T_2)$
    $\Rightarrow \textsc{NextLocation}(PNumID, T_2, Z)$

TABLE III: Rules for the model ROUTE-SEGMENTS and EVENT-AWARE SEGMENTS.

infer. To describe where a particular number is along a route segment, we introduce $\textsc{RLocation}(N, L, RS, T)$ which is 1 if number N is at location L, on route segment RS, at time T.

Initially, each location is randomly assigned to a route segment. These assignments are then updated according to the rules outlined in Table III which we explain next. This process essentially clusters the route segments, where route segments are grouped together according to some distance measure. For example, here we introduce rules which state that two locations might be on the same route segment if they are geographically close. Additionally, we constrain that if two locations are on the same route segment then a link should exist between them. However, this constraint is not hard, and it is possible that locations will be assigned to the same route segment, but not linked.

Like the predictive model described before, latent variable PSL models template graphical models. A difference is that in the latent setting the joint probability distribution is defined over the observed variables $\boldsymbol{x}$, target variables $\boldsymbol{y}$ and latent variables $\boldsymbol{z}$, where $\boldsymbol{z}$ is a vector of latent variables. To perform weight-learning with latent variables, we use the expectation maximization method described by Bach et al. [22].

Rule 1 in Table III expresses the prior belief that most locations are not on most route segments. Similarly, Rule 2 expresses that most locations are not traveled between. With Rule 3 we assign specific priors to locations being on route segments. For example, we seed each route segment with one seed location, such that w_{plr} is high. For all other locations w_{plr} is relatively low. The choices of seed locations are explained in more detail in Section V. For each location position X and each route segment RS we learn a weight for this location being on this route segment with Rule 4. With Rule 5 we express that if a phone number ID is at a location on a route segment, then that location is on that route segment.

Rules 6 and 7 transfer the spatial rules from the previous model into this new route segment discovery problem. Here, if two locations are close or in the same state, and each location is on the same segment, then a link exists between the two locations. Additionally, if two locations are frequently traveled between, then there might be a link between them, as expressed by Rule 8. As in the location prediction model we utilize similarities in ethnicity distributions. Here, with Rule 9, we express that if two locations have similar ethnicity distributions, then a link might exist between them. To express that LINKS should connect locations on the same route segment, we include Rule 10.

We infer a phone number ID's next location with Rule 11. For each location pair, we learn a weight $w_{l_1 l_2}$ which expresses the extent to which a number will move from route segment position at location l_1 to the location l_2. This rule has a similar functionality to Rule 1 in Table II.

As in SPATIO-TEMPORAL, here we constrain the values to $\textsc{NextLocation}(PNumID, T, X)$ such that a phone number ID cannot simultaneously be in two locations at the same time. Additionally, we constrain route segment positions such that a phone number ID cannot simultaneously be in two locations on the same route segment at the same time. The remaining rules in Table III are relevant for the event-aware route segment discovery model, which we discuss next.

C. Event-Aware Route Segment Discovery Model

Our final model, which we refer to as EVENT-AWARE SEGMENTS, is an event-aware route segment discovery model which consists of all of the rules in Table III. In this model we incorporate rules which can infer future locations given knowledge of events. Here, we encode the idea that instead of visiting environmentally affected areas, traffickers will visit neighboring locations on the same route segment.

To express that traffickers may skip affected locations and visit the next location on a given route segment, we develop Rule 14. To express that traffickers may reverse course, and visit a previous location, we introduce Rule 15. Here, EFFECTED(Y) is 1 if location Y was effected by a given event. To infer only those movements which occur after the event of interest, we introduce POSTEVENT(T) which is 1 if time T succeeds the date of the event, and 0 otherwise.

V. EMPIRICAL EVALUATION

In this section, we present our evaluations on two tasks: predicting future movements and discovering routes. We cast the prediction of future movements as a classification task, where we predict if a number ID will visit a given location. Locations are grouped together, such that groups are routes and each location is assigned to one route. Here, a route is a path such that multiple locations are visited in some temporal order. We begin this section with a discussion of the data.

A. Trafficker Movement Data

We compare our three proposed models, SPATIO-TEMPORAL, ROUTE-SEGMENTS and EVENT-AWARE SEGMENTS, on postings related to Hurricane Mathew and Typhoon Goni. In the case of Hurricane Matthew, we first collect phone numbers from postings made in locations in Florida from July to December 2016. We then collect all additional postings which mention these numbers in a time period from July 2015 to December 2016. This provides us with 17 contiguous months of movement data. In this second stage, these seed numbers can be in postings made in any location. Postings are made at a daily resolution, and the difference between two consecutive postings can range from daily to monthly. We then get a collection of K numbers, $N = \mathbf{n}^1, ..., \mathbf{n}^k$, where each $\mathbf{n}^i$ is posted in a location l at time t, $\mathbf{n}^i_{l,t}$. This process is repeated for Typhoon Goni, where we first collect phone numbers from postings made in the Philippines and surrounding locations from April to November 2015. In the second stage, postings which contain these seed numbers are collected from April 2014 to November 2015, providing us with 19 months of contiguous data.

On average, for the hurricane data extracted as described above, each phone number is posted in three locations. In the Philippines data, the average number of locations is five for each phone number. In Fig. 3 we see the number of traffickers which visit certain numbers of locations. As the number of locations increases, the number of traffickers posting in more than that many locations decreases exponentially. This relationship is stable across both datasets. That most numbers visit a small amount of locations suggests the presence, and perhaps predominance, of smaller organizations. This aligns with other reports which find that the majority of trafficking is conducted by small groups [17], [23]. However, this does not indicate that *all* trafficking activities are conducted by small groups.

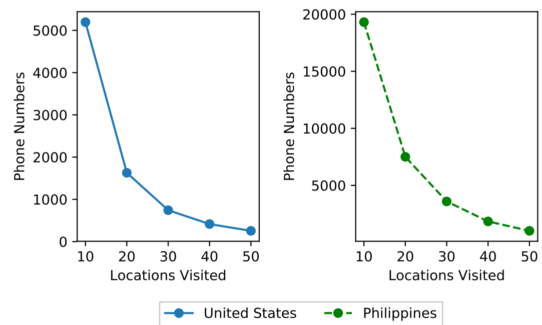

Fig. 3: Total phone numbers (on the y-axis) which visit more than a certain number of locations (on the x-axis).

Fig. 6 shows the frequency of movements between locations in the United States. As can be seen, there are some clear patterns between certain locations. These patterns can be utilized in predicting the next locations. The top source locations are Manhattan, NY, New York, NY[3], San Francisco, CA, San Jose, CA, and Westchester, FL. Travel most often occurred between Fort Lauderdale and West Palm Beach in FL.

In Fig. 5, we show the travel patterns in and out of the Philippines. Here, we see a striking difference from the United States data. Unlike in the United States, where there is a large amount of inter-state travel, in the Philippines, there is a lot of traffic between the Philippines and external locations. We also see that the most popular locations in the Philippines are San Mateo and Santa Ana. For each of these locations there are not large differences in the in and out degrees. The most common source and destination location for San Mateo is San Francisco, CA while the most common source and destination for Santa Ana is Los Angeles, CA. It is interesting that, at least for this subset of sampled data, that it's relatively uncommon to travel between San Mateo and Santa Ana.

Another difference between the two datasets is the distance between consecutively visited locations. This distance tends to be smaller in MATTHEW than in GONI. For example, the median distance in MATTHEW is 480 miles while it is 1246 in GONI. This illustrates the more international characteristics of GONI.

For the tasks of predicting future locations and discovering routes, we conduct several additional preprocessing steps for both datasets. We only consider postings with phone numbers that can be associated with a single location on the day of the posting. This step helps filter out those numbers which are posted in multiple locations simultaneously and whose

[3]If an advertisement differentiated between Manhattan and New York we kept that distinction.

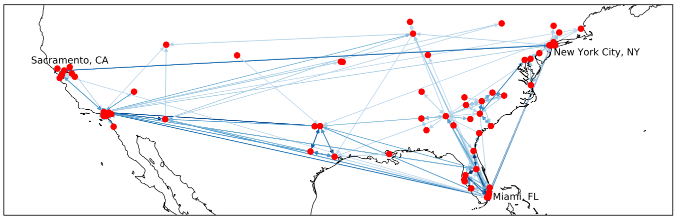

Fig. 4: Travel to/from locations in the United States. Edges are weighted according to number of trips on that edge. For clarity, we show only common trips.

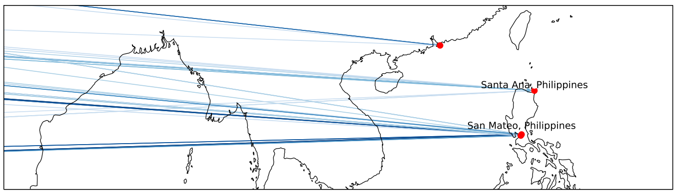

Fig. 5: Travel to/from locations in the Philippines. Edges are weighted according to number of trips on that edge.

location is thus ambiguous. Additionally, we only retain those numbers which are posted in at least three distinct locations at three distinct times. At test time, we infer the location of all phone numbers N at the time of Hurricane Matthew. We thus create a test set from all $\mathbf{n}^i_{l,t_h}$ where t_h falls on October 7th, 2016. We create a validation set from all $\mathbf{n}^i_{l,t_{h-1}}$ where for each $\mathbf{n}^i$, t_{h-1} is the time stamp which immediately precedes t_h. The training set is then all remaining phone numbers, $\mathbf{n}^i_{l,t_p}$ where $t_p < t_{h-1}$. This produces 2090 numbers, and approximately 18,400 postings. We refer to this dataset as MATTHEW. For Typhoon Goni, we choose August 22nd, 2015 as t_h. This results in a dataset of 6086 numbers and approximately 63,000 postings, which we refer to as GONI. In the following experiments we create a train, validate and test set for both MATTHEW and GONI. We split by phone number, such that 25% of all numbers are used as a validation set, and 25% are withheld in the test set and not seen in any stage of training.

We assess the ability of each model to predict the next location. In a real-world setting it is not clear how candidate next locations would be chosen. The simplest scenario would be to infer the most likely next location, out of all possible locations. To reduce the number of locations considered and generate a reasonable candidate set of next locations, we sample 10 potential next locations according to their great-circle distance to the current location. We additionally sample 10 locations from the same state, uniformly. In order to explore possible next locations which might not be geographically close, we randomly sample 10 more locations from the entire set of locations. This provides us with a small but reasonable set of 30 possible next locations for each location.

In inferring routes we initially randomly assign each location a route. These assignments are then updated by the model. For each route of k total routes we choose one seed location which belongs to this route with a high weight value. For these seed locations, w_{plr} in Rule 3 is set to 1000. These seeds are chosen as the top k locations according to the amount of outgoing traffic. For all remaining locations the initial route assignment is done randomly and for each location we set w_{plr} to 100 for exactly one randomly chosen route id. The value of k is then a hyper-parameter which we explore with validation data.

To measure the similarity in ethnicity mentions between two locations, we compute a histogram of counts for ethnicity mentions for each location, and then compute the *Kullback-Leibler*-divergence between them. We then translate the divergence into a similarity between [0,1]. Similarities are computed between all pairs of cities with non-zero counts of the top ten ethnicities across the entire dataset[4].

B. Evaluation of Location Prediction

We compare our three spatio-temporal models to a distance-based baseline, which we refer to as SPATIAL. This baseline simply chooses the closest next location from the same set of potential next locations as the other models. In Table IV, we show the F-Measure on the task of predicting next locations.

	F-Measure	
	MATTHEW	**GONI**
SPATIAL(Baseline)	9.37	8.57
SPATIO-TEMPORAL	71.0	74.8
ROUTE-SEGMENTS	**82.8**	**94.2**
EVENT-AWARE SEGMENTS	**83.4**	**95.1**

TABLE IV: F-Measure of each model on the location-prediction task. Bold signifies statistically significant improvements over both SPATIAL and SPATIO-TEMPORAL.

In addition to the F-Measure we consider the error rate, i.e. the fraction of phone number ids in the test set for which the predicted next location was incorrect. The ROUTE-SEGMENTS model improved the error rate from 28.8% (in SPATIO-TEMPORAL), to 17% for MATTHEW. In GONI, the improvement was even more pronounced, from 25.2% to 5.78%. Additionally, we saw that areas in the potential path of Hurricane Matthew were more difficult to predict, as they obtained an error rate of 29% in ROUTE-SEGMENTS. Incorporating event-aware rules provides a reduction in error, as EVENT-AWARE SEGMENTS achieved an error rate of 27% for these locations.

C. Evaluation of Discovered Route Segments

Next, we inspect the discovered route segments for each dataset. To determine the number of route segments that best fits the data, we search over different numbers of routes and evaluate with the validation set. For each dataset we evaluated on 3-30 segments, in step sizes of three. Each location can belong to a route-segment to some degree. For each location l, we assigned it to route-segment rs_i where the value of ONROUTESG(l, rs_i) was higher than all other ONROUTESG(l, rs_j), $j \neq i$. To construct routes, we consider

[4]The choice of ten was a hyper-parameter explored with training data.

all links, $l_i - l_j$, where l_i and l_j were on the same route segment and the value of $\text{Link}(l_i, l_j)$ was greater than .5.

In Matthew we found that nine route segments achieved the highest location-prediction performance on the validation set. In Goni, we found 24 route segments to best fit the validation set. In Matthew, the most common route segment originates in Los Angeles, CA and 57 phone numbers travel along some segment of it. In Goni, the most common route segment originates in San Francisco, CA, and 77 numbers travel along some portion of it.

Each dataset displays both regional and long-distance travel patterns. In Matthew, the most common segment is from Long Beach to Orange County to Los Angeles, CA. However, there are some cross-country trips, such as between locations in Florida and locations in California. The discovered route segments are more spread out in Goni. For example, there is a strong link between Dubai and Singapore.

In Fig. 6 we show a sample of discovered segments for Matthew. We focus on Matthew, as it is covers a more geographically concentrated area, and is easier to inspect visually. The color of each node corresponds to a route-segment id (it is best to view a color version of this plot) and edge opacity indicates link strength. We show all links with strength greater than 0.5. We can see some meaningful grouping of links in California with the cluster of green nodes. Interestingly, this is connected to a small group of green nodes on the eastern coast of the United States. We also see a cluster of orange nodes in Florida corresponding to a grouping of segments there.

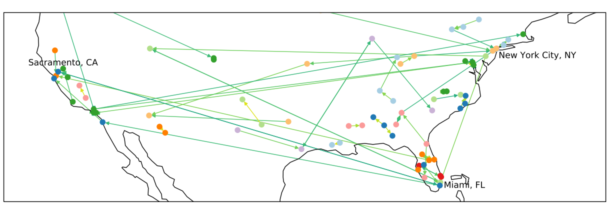

Fig. 6: Selected discovered route segments in Matthew.

VI. Discussion

We have proposed that extreme weather events can impact human trafficking, both through their impact on populations and locations. We saw that post-event there was evidence of an increase in the relative number of advertisements mentioning ethnicities from event-effected areas. Mentions of both Caribbean and Philippine ethnicities increased after Hurricane Matthew and Typhoon Goni, respectively. As the Philippines are a common source for trafficking victims, that we see substantial increases in Filipino ads in two locations suggests that traffickers may have taken advantage of environmentally induced vulnerabilities.

Readily available online data can provide surrogate statistics into the otherwise difficult to trace activity of human trafficking. However, there are many limitations with this data. One hindrance is that phone numbers are not maintained for long periods of time. Another limitation is that not all ads are posted by human traffickers. Furthermore, traffickers are not a homogeneous population and research in this area can be much improved by insight into how different trafficking groups operate. A particularly vital question is how such variations might be detected from the limited available data.

VII. Related Work

A critical task in understanding human trafficking is to extract relevant information from online advertisements. This task has been addressed by a number of publications. Szekely et al. [10] propose a knowledge graph approach to extracting attributes from ads, and deployed this system with law enforcement agencies. Portnoff et al. [11] address issues of authorship, utilizing Bitcoin as well as the posting service Backpage.com, to identify true post authors. Also addressing whether posts originate from the same authors Nagpal et al. [24] use a support vector machine classifier. To confront the challenge of successfully determining advertisement locations, Kapoor et al. [25] propose a constraint-based approach.

Another important task is determining which advertisements are truly cases of human trafficking. Alvari et al. [26] use an semi-supervised approach to detect ads with high risk of trafficking. Addressing both the challenge of extracting and utilizing data from online advertisements, Dubrawski et al. [12] use extracted textual features to detect incidences of trafficking.

There has been limited prior work on the question of how events can disrupt trafficking. Dubrawski et al. [12] establish a positive correlation between the Super Bowl and ads for trafficking. They also attribute a rise in trafficking to a population boom in North Dakota. Their work demonstrates the need to further understand how events can transform trafficking dynamics.

Similarly, the question of predicting traffickers' movements has been under-explored. Ibanez and Suthers [13] collected online advertisements and analyzed phone number patterns to extract circuits. They discovered several regional circuits, such as between locations along the West Coast of the United States. This work highlights both the spatial and habitual nature of trafficker travel.

In our work, we collect ethnicities, phone numbers, and locations from online advertisements. These entities can then be used to address relevant questions and tasks in this domain. Here, we address the novel question of how environmental events affect trafficking activity. As one approach to investigating this question, we propose a series of collective probabilistic models for predicting where traffickers will travel next.

VIII. Future Work

There are many remaining questions concerning the relationship between environmental events and human trafficking. Here, we have provided an initial investigation into this relationship. Future work might consider additional datasets and events. In this paper we investigated human trafficking in regards to sexual services. Human trafficking of labor, such as construction services, might be more closely connected to environmental events.

Discovering route segments should be seen as a first step in discovering routes along which traffickers travel for longer periods of time. In order to discover these routes, long-term data is required. Another important next step is to seek collaboration with law enforcement authorities who might be able to verify or inform the discovered routes. One important question is how best to detect when multiple phone numbers refer to the same trafficker, such information could aid in discovering routes as it would alleviate the problems caused by inconsistent records. Determining how to verify that multiple numbers truly belong to the same trafficker is also a subject for future work.

Our model can incorporate both spatio-temporal and behavioral knowledge, providing a flexible framework for fusing heterogenous data sources to understand complex events. This framework might prove useful in a number of related tasks, such as modeling the impact of extreme weather on human migration.

IX. Conclusion

Human trafficking is a serious social problem which demands scientific attention. We investigated how environmental events might impact human trafficking in three ways: by changing the vulnerability of environmentally effected populations, by changing the attraction of traffickers to effected locations, and by disrupting trafficking travel. In the aftermath of two separate events we saw increased relative ad mentions of effected ethnicities, supporting the idea that effected populations might be more vulnerable to trafficking after catastrophic weather events. Overall advertisements decreased in two effected locations in Florida, while this decrease was not consistent over time. To address the third research question we proposed a series of spatio-temporal predictive models. These models can incorporate both data-driven approaches, as well as domain knowledge such as how events might disrupt movement. Indeed, we saw a small improvement in predictive performance when incorporating knowledge of events.

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