MONITORING HUMAN TRAFFICKING IN DISPLACED POPULATIONS

A Thesis in
Information Sciences and Technology

by

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When people hear the word “slavery,” it conjures images of a terrible scourge on human history. They think of a despicable act perpetrated by human beings through the course of ancient and contemporary history, but history nonetheless. The sad reality is that slavery is alive and well in modern society. Dubbed “human trafficking” in lieu of more telling designations, forced labor and sexual exploitation have pervaded the human experience in higher volumes than any other point in recorded history.

In this paper, I explore human trafficking through the lens of a timely and relevant case study – Syria, in the midst of a bloody civil war and a massive humanitarian crisis, provides a number of challenges and difficult questions for humanitarian organizations and governments to ponder. Among those issues, human trafficking among displaced persons looms large. Humanitarian organizations, governments and other interested parties (such as the open-source mapping community) are actively involved in collecting data on the Syrian refugee crisis. However, given the difficulties inherent in monitoring trafficking cases, nothing significant has surfaced.

Using basic text mining, social network analysis, and mapping techniques to investigate the crisis through social media posts, my findings seek a proof-of-concept for counter-trafficking in persons (CTIP) methods going forward. It may be possible, in future work, to augment the traditional monitoring process for counter-trafficking in persons using electronic traces mined automatically from the Internet.
# TABLE OF CONTENTS

List of Figures .............................................................................................................................................. v  
List of Tables ................................................................................................................................................ vi  
Acknowledgements ..................................................................................................................................... vii  
Chapter 1 Introduction ............................................................................................................................. 1  
Chapter 2 Explication ............................................................................................................................... 4  
Chapter 3 Literature Review/Background ............................................................................................... 10  
  
Online Human Trafficking ..................................................................................................................... 16  
Electronic Traces in Social Media .......................................................................................................... 17  
Research Question ................................................................................................................................. 18  
Chapter 4 Research Design .................................................................................................................... 20  
Chapter 5 Data .......................................................................................................................................... 23  
Chapter 6 Methods ................................................................................................................................... 25  
  
Data Collection ....................................................................................................................................... 25  
Data Analysis .......................................................................................................................................... 28  
  
  Preprocessing and Pre-Testing ............................................................................................................ 29  
  Text Mining .......................................................................................................................................... 31  
  Social Network Analysis ...................................................................................................................... 33  
  Mapping .............................................................................................................................................. 35  
Chapter 7 Results ..................................................................................................................................... 37  
  
Text Mining............................................................................................................................................. 37  
Social Network Analysis ......................................................................................................................... 41  
Mapping, Location-Based Text Mining .................................................................................................. 45  
Chapter 8 Discussion ............................................................................................................................... 48  
Chapter 9 Conclusions ............................................................................................................................. 51  
References ............................................................................................................................................... 55
LIST OF FIGURES

Figure 1: The Global Human Trafficking Industry..........................................................11
Figure 2: The Syrian Refugee Crisis (HIU, Department of State).....................................21
Figure 3: Search Terms for get_tweets method............................................................26
Figure 4: Pre-Test Results...........................................................................................30
Figure 5: findFreqTerms() results...............................................................................38
Figure 6: findFreqTerms() results for "sparse" TDM....................................................38
Figure 7: findAssocs() results for "daddi" ................................................................39
Figure 8: findAssocs() results for "rape" ....................................................................40
Figure 9: Network Graph with most frequent nodes highlighted ..................................44
Figure 10: Network Graph with @IsaAbdullah91 highlighted.......................................45
Figure 11: Mapping results (global) .............................................................................46
Figure 12: Mapping results (bounding box only).........................................................47
Figure 13: findFreqTerms() results for tweets inside bounding box.............................47
LIST OF TABLES

Table 1: Frequency of Tweets by Language ................................................................. 37
Table 2: SNA Results (overall graph metrics) ............................................................... 42
Table 3: SNA Results (degree and centrality metrics) .................................................. 43
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Chapter 1

Introduction

People are lured and coerced into modern-day slavery at an alarming pace. We call this “human trafficking” in lieu of more telling designations. This term is an umbrella under which several equally-grievous criminal activities reside. Human trafficking may refer to “forced labor,” where persons are either enslaved against their will and put to work or handed an impossible choice between dangerous working conditions for impossibly low wages and their own demise (their families are likely threatened as well). On the other hand, human trafficking may refer to sex trafficking, a practice whereby people (typically young females) are kidnapped and forced into an existence as sex objects without any say in the matter.

In this project, I will explore the umbrella of human trafficking through a very particular lens. Just as trafficking may refer to several activities, those activities affect some populations and situations differently than others. One context where even the most basic descriptive research appears lacking is the trafficking of persons in refugee camps. Refugee populations are displaced, often living in poor conditions, and sometimes lacking basic needs when camps exceed their capacities. This makes an ideal scenario for traffickers aiming to prey on withered, weakened targets wandering far from home. The data necessary for us to begin understanding the extent and, perhaps, the cause of this corner of the trafficking umbrella is virtually nonexistent.

What we do have, however, is a timely and relevant case where an ongoing refugee crisis has produced numerous reports of human trafficking incidents. Syria, in the midst of a bloody civil war and a massive humanitarian crisis, provides a number of challenges and difficult questions for humanitarian organizations and governments to ponder. Among those issues, human
trafficking in refugee camps looms large. Humanitarian organizations, governments and other interested parties (such as the open-source mapping community) are actively involved in collecting data on the Syrian refugee crisis. However, given the difficulties inherent in monitoring trafficking cases, nothing significant has surfaced thus far. With traditional means of monitoring and thwarting acts of modern-day slavery once again dropping the ball, we have to get creative. Prior work on traffickers and other similar criminal operations has suggested that web analytics can augment traditional law enforcement and humanitarian efforts. Not only do the perpetrators often use online classifieds and social media to ply their trade, but it may be possible to uncover reports of trafficking incidents or indicators of vulnerability in specific populations by monitoring open source electronic communications and web documents.

Using the situation in Syria as a case study for better understanding trafficking among displaced populations, I will employ several web-based monitoring methods in an attempt to augment existing monitoring practices. The result, if this project is successful, will be a proof-of-concept for using electronic traces in web data to help improve the quality and timeliness of the monitoring of human trafficking.

The scope of this project is such that not every avenue of web analytics that is applicable to the human trafficking phenomenon will be explored. While I will make a point of highlighting many potential sources and methods of capturing relevant electronic traces (including social media, online classifieds and web documents), I have settled on Twitter as the primary data source for evaluating the monitoring methods developed through the rest of the project. When an ongoing news story becomes a topic of global interest, Twitter often becomes a place for widespread discussion on that topic. A running capture of tweets using the keyword “Syria” will often produce tens of millions of tweets per day (or, even, per hour). Early examinations of our capture suggest the potential to uncover, at the very least, indicators of vulnerability in specific geographic areas. If time permits me to explore potential sources of electronic traces relevant to
monitoring human trafficking, I may take them up as well. Given constraints on time and resources, I believe that Twitter is an excellent starting point.
Chapter 2

Explication

To avoid confusion and strip away excess meaning in my primary research question, I first want to “explicate” several items that might otherwise leave room for ambiguity. Taking this extra step to define both the topic and the research question(s) is immensely beneficial. When we know exactly what it is we are measuring, we avoid pitfalls for internal validity. This is a problem for many studies, where the extent to which researchers actually measure what they mean to measure is low and the findings are drastically diminished. Furthermore, explication can be used both for selecting an appropriate theoretical definition for a concept (or, making one up ourselves based on a review of other definitions) and devising an appropriate operational definition. I will model my explication after the guidelines set by Chaffee, as well as several other excellent examples that were introduced to me through coursework and independent research.

The result of this process, hopefully, will be a sufficiently narrow problem space from which I can derive reasonable conclusions whilst answering my research question. Explication will take me from “human trafficking” to a specific subset of trafficking that leaves no misunderstanding as to what I am actually trying to measure. Another significant benefit of explication is obtaining concurrent validity with other operationalizations of concepts that do not easily lend themselves to operational definitions. For example, I will reap the benefits of this process when I attempt to operationalize things like “vulnerability” to trafficking.

Human Trafficking

There are a number of working definitions of human trafficking, though I believe we should first turn to international law enforcement and policymaking bodies because they have
both more experience and more authority to monitor and address human trafficking incidents than other interested parties. The UN Office of Drugs and Crime (UNODC) defines human trafficking as the “acquisition of people by improper means such as force, fraud or deception, with the aim of exploiting them.” There are two absolutely critical elements to this definition that make perpetrators of human trafficking incredibly difficult to convict: the modifier “improper” before “means,” and the addition of “aim” or intent. In a subsequent paper, UNODC outlines three necessary elements that define a trafficking incident: the act itself, the means (from a pre-defined set) and purpose. Attaching these modifiers distinguishes the crime of trafficking in persons from others such as smuggling migrants, although the latter can certainly become the former in the blink of an eye. UNODC varies their language slightly depending on which publication you read, but the themes of matching the act of trafficking to crooked means and a malicious purpose remain. For our purposes, we can limit our problem space to incidents where these modifiers are evident.

Another international body with a keen interest in clearly defining human trafficking is the International Labor Organization (ILO). The ILO operates with a working definition taken from a mid-90s United Nations (UN) convention on transnational crime referred to as the “Palermo Protocol.” Several acts are included to mean “trafficking”: recruitment, transportation, transfer, harboring and receipt. Additionally, the victim needs to be “exploited.” This means that they must not have given consent to the aforementioned acts. There are exceptions for children, whereby prosecutors need only prove that the act took place regardless of means or intent (UNODC also makes this clear through other publications). The biggest distinction here is that there are no clear shouts about “intent,” whereas UNODC prefers to include purpose as a necessary criterion before pursuing a trafficking incident.

A third international body with a major stake in human trafficking is the United Nations High Commissioner for Refugees (UNHCR). Whereas UNODC takes a law enforcement
perspective to the problem and ILO has a focus on creating legal standards to prevent forced labor, UNHCR is uniquely interesting to me because they are engaged in the protection of refugees. Their interest in human trafficking only extends as far as preventing such crimes among displaced populations (the goal of this research, as it were). Given this focus on protecting the victims of trafficking and the fact that trafficking, according to the UN at large, does not fall under the mandate of UNHCR, the commissioner does not go so far as to offer a unique definition of trafficking. It is worth noting, however, how the term is treated in context throughout several UNHCR publications. The means and purpose of perpetrators is, once again, absent. UNHCR throws a bit of a proverbial blanket over the potential acts that could be considered “trafficking” by UNODC and other stakeholders to include forced labor, sexual exploitation and any other “harmful” actions taken toward persons that fall under UNHCR’s mandate. For our purposes, it is interesting to see these distinctions between a law enforcement body and two international organizations driven by a mandate solely to protect trafficking victims. As we are looking to monitor these incidents as a whole, our working definition of human trafficking should include the actions, means and intentions of the perpetrator.

The US Department of State has several offices across multiple bureaus that are engaged in anti-trafficking activities ranging from raising awareness to pursuing traffickers and even conducting research on how to develop better indicators and monitoring practices. They defer to both US and international law whilst defining the problem, and are sure to include the full range of acts (recruiting, harboring, etc) and means (they specifically cite the “goal” of traffickers) employed by perpetrators in a trafficking incident. Again, for our purposes, I would argue that a “holistic” approach to any trafficking incident demands that we at least examine and consider the means (ranging from more subtle coercion to deception and outright violence) and the purpose (specifically, to “exploit” victims) of traffickers along with the actions taken by both perpetrators and victims. Based on the work that I have done leading up to this proposal, I anticipate that I will
uncover a number of cases where only some of that information is clear. By the letter of the law, trafficking incidents where adults are the victims require a high burden of proof on law enforcement officials because simply observing the act is not enough. Trafficking victims can be touted in plain sight through public places in certain parts of the world while law enforcement officials are helpless to aid them where both “means” and “intent” of traffickers are not clear.

From a researcher’s perspective, those cases are still interesting. They complicate the process of operationalization because counting “incidents” of human trafficking demands this sort of explication. Nevertheless, I believe it is worth “counting” or at least exploring traces of trafficking practices in our data should they arise. It may well be that adding information scraped from electronic traces might fill in the blanks and shore up the definitional constrains faced by those with the authority and means to actually combat human trafficking hands-on.

Moving from legal definitions to operational definitions requires that we shift our search from legal and regulatory bodies to academic research. UNODC implicitly gives us an operational definition of trafficking incidents as legal trafficking cases brought before a recognized court. I say this because while, in theory, UNODC probably considers any actual trafficking incident (reported and prosecuted or not) as a human trafficking incident. Still, their only operationalization comes in a case law database of trafficking incidents that only includes cases that were legally prosecuted\(^5\). As you might surmise, this leaves us with a stunning lack of data. For our geographic case study, UNODC has exactly zero trafficking incidents to report. The effort is very young and much appreciated given the lack of other data sources, but we would be committing ourselves to missing metric tons of data if we operationalized human trafficking solely through prosecuted cases (can you imagine an abduction in a refugee camp going through internationally-recognized due process?).

In a criticism that shares many of my concerns with the UNODC and ILO definitions of human trafficking, Hoyle et al cites a penchant for focusing on the willingness of victims as the
defining factor in the operationalization of trafficking incidents. This limitation precludes victims who find themselves trapped by deception, willingly walking into a situation without knowing or understanding the implications and subsequently finding themselves enslaved for either forced labor or sex trafficking. The authors here also note that, based on prior surveys of trafficking victims, cultural attitudes toward slavery played a role in the initial willingness (or lack thereof) to participate in potentially dangerous situations. That kind of susceptibility might be mitigated through awareness, but limiting our operational definition of human trafficking based on the initial willingness of victims risks cutting out an untold number of incidents and potentially ignoring important electronic traces or reports. These concerns are shrugged off by Smith and de la Cuesta for the sake of “clarity,” as it is admittedly difficult to monitor the willingness of victims in different stages of a trafficking incident. These authors were comfortable discarding cases where victims initially willingly entered the employ or control of traffickers as “smuggling” incidents, although they do not address the former’s arguments about deception and coercion making a victim’s initial willingness to enter a situation unusable in distinguishing trafficking from migrant smuggling.

Another interesting operationalization of human trafficking comes from Jac-Kucharski and is based on applications for “Tvisas.” These are specially issued visas for trafficking victims handed out by the US Department of State. This author examined patterns in the issuance of Tvisas by country of origin and used a regression model to identify indicators that produced higher and lower numbers of Tvisas (both applications and issuances). Given what we know about the demographics of trafficking victims and the conditions that they are held under (namely, many are unable to free themselves or are held indefinitely), we might argue that many trafficking victims never have a chance to apply for such visas or, perhaps, have never heard of them. Still, this is an interesting way of framing trafficking incidents that allowed researchers to shed some light on high-level trafficking indicators. For this project, it might suffice to search for
electronic traces that include discussion of Tvisas as, coupled with traditional law enforcement practices, we might be able to unearth and monitor trafficking incidents that would otherwise fly under the radar.

In an overview of methodological challenges to researchers studying human trafficking incidents, Tyldum and Brunovskis argue that the UN’s definition of trafficking is “ambiguous” in that it does not clarify grey areas such as prostitution and “positions of vulnerability.” These authors propose breaking victimization into stages so that we might address cases where a victim either begins or ends the process willingly. For example, we have already mentioned the prospect of victims being lured into seemingly legitimate work (including prostitution) before traffickers reveal their true intentions. Moreover, victims may be offered a “legitimate” way out or be reluctant to admit past trafficking incidents for either cultural or personal reasons. Again, this speaks to a holistic definition of trafficking incidents in lieu of better data. If we place limits on either the victims “stage” in the process or the mental workings of perpetrators, we are potentially leaving vast numbers of cases in the dark.
Chapter 3

Literature Review/Background

According to the International Labor Organization (ILO), there are roughly 20 million persons living under forced labor, based on ILO’s definition of forced labor\textsuperscript{xiv}. According to estimates from the US Department of State, around half of those are located in East and Southeast Asia; although the highest prevalence per capita lies in Eastern Europe (~4.2 persons per 1,000 inhabitants). The total number of persons that have succumbed to human trafficking, in one form or another, is estimated as high as 30 million, with 80% of those victims being female. Half of those female victims are under age 16, with the mean age estimated between 12 and 14\textsuperscript{xv}. The United Nations Office of Drugs and Crime (UNODC) estimates that the global human trafficking “industry” rakes in about $32 billion annually, making it the second-highest grossing criminal market behind drug trafficking. According to UNODC, the traffickers themselves are mostly male, although the gender split is perhaps less severe than we might imagine (42% of “recruiters” are female)\textsuperscript{xvi}. The problem is by no means limited to vulnerable populations abroad, as estimates of sex trafficking cases in the US have reached up to 2.4 million\textsuperscript{xvii}.

Traffickers themselves are an especially difficult bunch to monitor. UNODC reports that about two thirds of convicted traffickers from 2007-2010 were male\textsuperscript{xviii}. This does not come as a surprise given the aims of most traffickers, but the proportion of convicted female traffickers is very interesting to me (~33% of the total). Moreover, female traffickers were used most often whilst trafficking girls according to the same report. The demographics of perpetrators also vary by region. In Eastern Europe and Central Asia, for example, 75% of convicted traffickers are women and the majority of those women are local nationals. In Europe in the Middle East,
however, many foreign nationals act as facilitators of human trafficking. The motivations of these men and women are largely unknown to us because, unless they are prosecuted, traffickers are a well-hidden deviant population.

Figure 1: The Global Human Trafficking Industry

Research on hidden populations raises a number of methodological challenges. Atkinson and Flint suggest a “snowball” strategy whereby a series of samples and interviews eventually lead to the target population. This is, unfortunately, not practical for this project given time and resource constraints on the investigator as well as the lack of incentives for traffickers to submit to researchers. They are a tight underground community that makes over $30 billion annually and I cannot imagine that even a persistent series of “snowballing” samples and interviews would lead to a valid study of human traffickers.
Lazos notes the importance of ‘local knowledge’ in understanding human traffickers as a population. This is especially helpful for our purposes as Twitter grants us firsthand access to conversations and reports at the local level, as well as messages from the Syrian diaspora that derive directly from what is happening in country and throughout refugee camps. In terms of unearthing traffickers as hidden deviants and understanding the nature of their deviance, however, that is another vast challenge to contend with. Klingemann sheds some light on this challenge, arguing that seeing hidden deviant populations almost mandates political interest and political control. This is a compelling argument; however I would caution that it was written a decade before Twitter existed and that the author operates in the context of substance abuse. Especially in our case, where the country in question is in the midst of a full-blown civil war and the traffickers operate outside national political boundaries, the idea of exerting political control to make them visible does not seem feasible. Were it possible, governments would have found a way to empower law enforcement and halt traffickers some time ago.

On the subject of law enforcement, it is interesting to examine their difficulties in pursuing traffickers for prosecution because, unlike researchers, they have both a higher burden of proof to meet and a more direct stake in thwarting the perpetrators. Spencer and Broad argue that, in some cases, it is simply a lack of “zeal” that inhibits anti-trafficking efforts among local and national law enforcement bodies. There may be some merit to this argument, but the authors lack the data to support this claim. Law enforcement in Syria and the surrounding countries operate in a much different context than what we are used to as westerners. Furthermore, the region (Syria, Lebanon, Turkey, Iraq and Jordan) is caught in the midst of a civil war and an unprecedented refugee crisis with millions in need of assistance. It is difficult to assess their “zeal” in regards to human trafficking in such a complex situation without any data supporting such claims. A more logical explanation comes in a case study from Breuil et al, noting the troubles of Dutch law enforcement in monitoring and combating human trafficking.
within their own borders\textsuperscript{xxiii}. This study highlights the sheer skill of traffickers, with Dutch case officers often left multiple steps behind their marks due to an information gap. This is very interesting to me, as I wonder how such a gap might be closed using information drawn from electronic traces.

The information age has not made this problem any easier to solve. The internet provides traffickers with the right technical expertise an “electronic cloak” under which they can freely operate without fear of being exposed or stigmatized by the rest of the world\textsuperscript{xxiv}. I would argue that, for traffickers, this cloak extends offline due to the secrecy and, often, the invisibility of the trafficking community. Becker also notes that deviance is often understood contextually\textsuperscript{xxv}.

Underneath this electronic cloak, traffickers may not see themselves as deviants. Underneath the curtain that shades the trafficking industry, traffickers may not see themselves as deviants. Both of these arguments complicate traditional monitoring efforts, as traffickers are probably less likely to reveal their motivations and techniques to “outsiders” (either law enforcement or researchers) if they do not see themselves as morally or ethnically repugnant.

Further complicating our understanding of traffickers as a hidden deviant population, the makeup of convicted traffickers and general trafficking practices change drastically across regions. The disparity in gender among traffickers in different regions has already been noted (up to 75\% are female in Eastern Europe and Central Asia, while the overall percentage of women among convicted traffickers is about 33\%). In a publication alongside their Global Trafficking Report, UNODC noted key differences in the types of exploitation and flows of victims in various regions\textsuperscript{xxvi}. In Europe and Central Asia, victims are predominantly females exploited for sex trafficking. In Africa and the Middle East, roughly 68\% of victims are children. The plurality of victims in the Middle East (50\%) is exploited for forced labor, although a sizeable proportion (36\%) is subjected to sexual exploitation. Globally, trafficking flows are 50\% intraregional, with only 25\% of victims moving between different regions. Victims are typically trafficked from
poorer countries to richer ones, and 75% of all operations are “medium to short range.” The Middle East is unique in that 70% of trafficking victims are inbound from outside the subregion (35% from East Asia, 23% from South Asia, 20% from Africa, 10% from Eastern Europe and Central Asia). The International Labour Organization conducted a massive qualitative study on human trafficking in the Middle East, interviewing 653 adult men and women about the status of trafficking among adults. They uncovered deception as the most prominent tactic for traffickers to recruit victims in the Middle East, although the study has several glaring limitations that force me to take this very interesting conclusion with a grain of salt. First, 68% of trafficking victims in the region are children. The study focused on adult victims of forced labor, cutting out both child victims and victims of sexual exploitation at all ages. What these reports leave us with, ultimately, is a surface understanding of victimization in the region where our case study takes place. That is not to say that human trafficking in displaced Syrian populations will follow patterns identified by either UNODC or ILO. There are well over a million displaced persons in need of assistance scattered across both Syria and the surrounding countries, with refugee camps regularly exceeding their capacity by 100-150% according to the US Department of State.

Our case provides a unique opportunity for traffickers in the region, and I would be hard-pressed to believe that the perpetrators in the Middle East would not take advantage of such vulnerability.

This concern is well-supported by a long history of human trafficking among refugees and internally displaced persons. The mere status of displacement in a population is cited as an indicator for vulnerability by UNODC, UNHCR, ILO and the US Department of State. Still, we do not need to look far to find empirical support for the uniqueness of displaced populations in terms of vulnerability to traffickers for both forced labor and sexual exploitation. Kastrup uses a vast array of secondary data to overview trafficking and related abuses among displaced females, noting that such victims were more likely to be physically abused and subjected to sexual exploitation than non-displaced females. The study does not specifically address the Middle
East and mostly ignores male and child victims, but the factors leading to increased likelihood of abuse and sexual exploitation are in no way unique to female victims and I do not think it is a stretch to generalize these findings to other displaced persons. Moore, in an effort to discover a causal explanation of the “under-identification” of refugee trafficking victims, concluded that her “intervention mapping” approach would allow health professionals on the ground in humanitarian environments to better identify and monitor trafficking cases. This dissertation takes an admirable approach to a corner of the trafficking problem, but our focus is to discover traces of whole trafficking incidents rather than focus on identifying victims. The use of “mapping” here does not include GIS technologies, which leaves an interesting opportunity for the open-source mapping community and humanitarian organizations to consider. For my purposes, the lack of identification of victims does not suffice as a causal explanation for the unique vulnerability of displaced populations to human trafficking operations.

Perhaps a the best case for what makes displaced persons uniquely vulnerable to traffickers comes from Wilson, who notes both the physical (illness, age, lack of physical protection), social (isolation, stigmatization), economic and political disadvantages faced by our populations of interest. She specifically discusses how refugees are treated as commodities by those who are meant to protect them, and how that extends to commodification by traffickers. The situation in Syria has become a political battleground for several countries, both internationally and domestically. The US is a great example, where policymakers with competing agendas have tried to use the US foreign policy toward Syria as a lightning rod to hurt their opponents politically. Lost in those arguments, the refugees themselves are subjected to all of the disadvantages noted by Wilson and well-documented by UNODC and UNHCR.
Online Human Trafficking

Human trafficking efforts know no bounds, with online classifieds and other forms of electronic communication used to solicit new customers. In this particular study, researchers found that a stunning percentage of juveniles exploited for sexual purposes were discovered online (~20%). Furthermore, it appears that traffickers are willing to peddle their wares in great volume (upwards of 14K classifieds were discovered on one site alone). Other online classifieds, namely Craigslist, have been identified as hotbeds for trafficking activity. Furthermore, while existing work tends to lean toward online classifieds, there is evidence that both social media services and YouTube have been used as platforms for traffickers to ply their trade. Major also notes that perpetrators can use Twitter to employ deception against potential trafficking victims, recruiting them through seemingly-legitimate offers and building up trust over time.

In a broad technical effort to use electronic traces to combat sex trafficking, Wang et al note that both online classifieds and social media are prominent tools for traffickers to recruit and snare child victims. These authors developed TrafficBot, a system using natural language processing and information retrieval technologies to search for trafficking incidents and support law enforcement. They were able to successfully collate aliases and identifiers to point law enforcement to traffickers’ offline identities. Using a support vector machine (SVM) to automatically “learn” patterns of posts and build a database of potential victims and perpetrators, these authors demonstrated an advantage over traditional monitoring methods. For my research, this is a landmark demonstration of how even simple web analytics can significantly augment existing law enforcement practices and oust traffickers. Of course, this is applied to minors using the internet. In our case study, internet access among the population of interest is severely limited, although it is possible that traffickers are using the same tactics that authors have noted elsewhere and therefore might be discovered through electronic traces.
Electronic Traces in Social Media

Moving closer and closer to Twitter itself as a means for both traffickers and anti-trafficking parties, Wang conducted a study of SNAPSHOT, an online anti-trafficking initiative in China that operates on Weibo, the Chinese equivalent of Twitter. They found that young, well-educated persons were most likely to participate in the program as well as a reluctance to engage in offline trafficking initiatives. These motivations are interesting, but the critical elements of this study for our purposes are the workings of SNAPSHOT. Participants would take pictures of children that appeared as though they might have been trafficked and upload those under a specific designation in Weibo. The idea was to reunite those children with their families. Participation in the program absolutely skyrocketed within days, with thousands of pictures uploaded from every corner of China within a year of launching the initiative. This speaks to the lure of social networking for potential activists who might be reluctant or unable to otherwise participate in anti-trafficking initiatives. It is also interesting to note that all of this happened despite the known censorship and online monitoring practices of the Chinese government. It is impossible to say how a similar initiative would fare in the Middle East or in the Syrian case specifically, but these results speak to the power of social networking in the face of human trafficking.

Huyghe specifically cites Twitter as a tool for raising awareness on behalf of vulnerable populations and reducing vulnerability to human trafficking in a set of recommendations for businesses to combat traffickers. This is not a conclusion that is specific to refugee populations or our geographic area of interest, but it does speak to a broader acceptance of Twitter as a tool to raise awareness against traffickers. While I agree that it sounds a bit campy, he is not alone in citing awareness as a critical means in outing traffickers and protecting vulnerable populations. Dixon sees social networking sites as both a tool for traffickers and
an opportunity to thwart them, noting prior cases where traffickers recruited victims via social media and the technical means that might be undertaken to snare traffickers themselves\textsuperscript{xii}. Without using the term “electronic traces,” there is still support for the possibility of discovering previously unseen data on both victims and perpetrators using web analytics. That these authors specifically cite social media is especially encouraging for what we may or may not discover in the Syrian case.

**Research Question**

Now that we have a better understanding of the “state of the art” in human trafficking research as it relates to this project, including the limitations of existing work, I propose the following research question:

*Given the difficulty in monitoring human trafficking among vulnerable refugees and internally displaced persons, can electronic traces in social media help improve the quality and timeliness of the monitoring of human trafficking?*

Before moving on to the means by which I intend to answer this question, I would like to unpack several elements for clarification. First, “electronic traces” is an intentionally vague designation. I am not entirely sure what there is to be found in the chunk of the “Twittersphere” that has spent the last several months obsessively covering, reporting on and discussing the events in Syria. Data mining may eventually unearth evidence of traffickers or trafficking victims in our capture, but it is more likely that we will see snippets of information that, together, color indicators of vulnerability at a more granular level than prior work has attempted. What I mean by this is that we will find indicators at the individual level of analysis, where reports and communications in our dataset are coming directly from either primary sources or are relayed from those sources. This is distinct from existing research that relies on either secondary data
from the likes of UNHCR, UNODC and ILO or data unrelated to trafficking that provides regional and country-level indicators for vulnerability in displaced populations.
Chapter 4
Research Design

Understanding the scope of the global human trafficking industry, as well as the massive number of refugees dispersed across the world, it seems that it would be prudent to focus this effort on one case where those phenomena cross paths in order to fully grasp the context of the available data. I have chosen Syria as a case study not only because of its timeliness and relevance to this problem, but also because I have enough of a background on the region that I am comfortable tackling the nuances of the Syrian refugee crisis. The potential loss in external validity that is inherent in focusing so closely on one case will, in my opinion, be entirely surpassed by the assurance that I am actually understanding what I intend to understand. If there is a natural tradeoff between internal and external validity here, I am choosing the former given the limited state of existing research on human trafficking among displaced persons. Were there decades of excellent descriptive work already in place, perhaps we could broaden the scope of this study and attempt to find a more generalizable set of conclusions.

Furthermore, while there is still a lack of hard data and access to primary sources on the ground via traditional research and monitoring methods, there is no lack of coverage if we are willing to dig for it. There are several ways to follow the Syrian crisis over time, and the news is only one of them. The Syrian diaspora is extremely active, accounting for billions thus far in relief funds and acting as a key source of information for journalists and relief efforts worldwide. Between prior work discussed in the literature review and the sheer mass of our data set, I am convinced that the global online conversation (defined by electronic traces in social media) on Syria rivals any other major events in international relations. It is a case that
begs to be described and explored from a researcher’s perspective and, as far as trafficking incidents among displaced persons go, Syria appears generalizable to other populations in need of similar assistance.

If trafficking data is poor, trafficking data for refugees and internally displaced persons is even poorer or, in the case of Syria, virtually nonexistent. Displacement implies vulnerability to
trafficking according to UNODC, but that is a claim without a warrant. There are accounts of trafficking victims that surface at alarming rates from journalists and activists in the Syrian diaspora, but that is as far as we can see. The Syrian case provides a tremendous opportunity to begin understanding the actual extent of human trafficking among displaced populations and describe the problem with hard data. The timeliness of the case offers a chance to capture the full scope of electronic traces (tweets, specifically) without missing any context (as we might in historical cases).

A case study was chosen based on De Vaus’s work on the relationship between research design and data collection methods⁴⁹. My collection methods, discussed at length in the following pages, are specific means by which I will attempt to understand the Syrian case. That understanding, subsequently, will shed some light on my research question.
Chapter 5

Data

Twitter is a popular microblogging tool that allows users to write about their topic(s) of choice and converse with other users via short (140 character-maximum) statements, dubbed “tweets.” Users have several options for participating in conversations with friends and followers as well as other users (with no “follower” relationship necessary). One means of communication, “direct messaging,” is private and thus left out of our analysis. The primary public method for conversation is a “mention,” or the tagging of another user in one or more tweets. Users may also re-blog others’ tweets by “re-tweeting” them. Prior work has made the case for re-tweeting as conversation, citing the implicit messages sent to both the original sender and the followers of the user re-tweeting the original message. This is further validated by Sundar in 2008 with theoretical justifications for considering receivers as the source of interactive media communications\textsuperscript{xlvi} -\textsuperscript{xlvii}.

With several options for communicating with other users, Twitter is a ripe outlet for online conversation. We see this both in the availability of conversational tools (mentions, re-tweets, direct messages) and the sub-networks where communication is possible. Users are presented with their own personal “timeline,” where tweets from others they have chosen to follow (subscribe to) are visible chronologically. Network structure, in this case, is determined by follower-followed relationships and will not likely changed based on network traffic or the occurrence of various offline events. “Search” networks, however, are based on topics and therefore not limited to the follower-followed relationships that define user-based sub-networks. Search networks are tied together either by “hashtags” followed by a specific phrase or, simply,
the use of a common phrase. Twitter users can explore these search networks to find other users with common interests, either to follow or simply converse with.

In addition to the text of tweets, Twitter attaches metadata that can be collected alongside text. The username behind each tweet, any other usernames mentioned in the tweet, the date and time, and (when users give permission to Twitter) location are all logged automatically. Though a very small percentage of tweets (“somewhere between 1 and 2 percent” according to Twitter) are geotagged, it is very likely that any tweets matching both our keyword parameters and location parameters will carry relevance to the project. For example, if we capture 2 million tweets including one or more of our search terms, it is likely that around 20,000 tweets would also be geotagged in a location of interest. Those tweets (matching both parameters), in my opinion, will be more likely to involve actual trafficking cases than tweets that only match our text parameters.
Chapter 6

Methods

Data Collection

Twitter provides developers and researchers with several tools for mining tweets and associated metadata. I employed the streaming API, dubbed “Phirehose,” to capture electronic traces in real time. Phirehose, true to its name, allows users to access incoming tweets as they are created rather than giving us the option to query some preexisting database. For this project, that meant that we needed to access the streaming API in a timely fashion (lest important data become lost in the “ether”). Moreover, Phirehose itself is only a tool to access tweets. Users must use their own program(s) to actually collect and store information as Phirehose makes it accessible.

Based on recommendations from colleagues and a brief search of available options, I selected 140dev, a tool that gives researchers many options for capturing and parsing tweets from Phirehose\textsuperscript{lviii}. 140dev needs to be implemented on a machine that can manage a constant stream of requests and store the incoming data. In this case, I used a virtual LAMP server to create the necessary environment for continuous, automated data collection. The LAMP software bundle includes a Linux operating system, Apache HTTP server, MySQL database management system, and the PHP scripting language (hence the acronym).

140dev uses two scripts (“get_tweets.php” and “parse_tweets.php”) to physically collect and organize tweets respectively. The get_tweets script requires specifications for keywords and, optionally, locations for each running capture.
Our first specification for the get_tweets script is a list of keywords or search terms for 140dev to pull from Phirehose. Any tweets containing any of the specified keywords are thereafter “captured” and stored on the LAMP server. This process is continuous once it has been initiated, so the user does not need to be present and/or logged in to sessions with any aspect of the system during the collection phase.

These terms are by no means a comprehensive or otherwise ‘perfect’ collection. There is, unfortunately, not much of a precedent for such a list in the existing body of work on human trafficking. The terms were selected based on the literature review, consultation with colleagues and subject matter experts, and one primary source xlix. From these sources, I drew up a list of over 200 unique terms tied to human trafficking. I eliminated terms that were too vague (i.e. words that have just as much significance outside the human trafficking community) so that the data
collection tools would not be overwhelmed with irrelevant tweets. The ‘final cut’ of the list, pictured above, was meant to eliminate redundancies and collect the most relevant data possible.

Initially, based on prior experience with Twitter and the literature review for this project, I allotted 7 days for each phase of data collection. Within 4 days, the memory on the LAMP server had hit capacity, stopping the first collection phase. At that point, the system had pulled over 2 million tweets using our chosen search terms. Given the enormity of the dataset at that point, I decided to end the phase at 4 days rather than 7. The subsequent sessions were also held to 4 days for the sake of validity.

There were three distinct collection sessions. The first session employed our search terms in English. The second session employed a transliterated version of those terms. Transliteration, here, means that the English terms were translated to Arabic using Google Translate before “Romanizing” the Arabic characters using a similar online tool (mylanguages.org/arabic_romanization.php). The results at each phase (the translation and transliteration) were reviewed by a proficient Arabic speaker. This “Romanization” is quite common on Twitter, as Arabic characters are not built in to the ASCII character set and most keyboards are designed for Latin characters. The third collection phase included location parameters. 140dev allows users to set a bounding box using two sets of coordinates (the southwest and northeast corners of the box, respectively) and limit keyword captures to that geographic space. Most tweets are not geolocated, and the tool can be lenient with its geographic limits, but this was a valuable capture nonetheless.

After the get_tweets script collects the “raw” tweets from Phirehose, a second method (parse_tweets.php) arranges them into a pre-set database schema. The schema includes tables for tweets (the text), usernames, “mentions” (aka interactions), tags, and URLs. All captured tweets are included in the “tweets” table. Only tweets that include mentions, tags, etc are included in the subsequent tables.
The phpMyAdmin operating system, accessible through a web browser or PHP shell, allows users to perform a number of operations on the database as get_tweets and parse_tweets run in the background. Two important functions, query and export, were especially relevant to this project. SQL commands were used to clean and optimize tables when memory became an issue, and also during the data analysis phase. The ‘export’ function in phpMyAdmin allows users to move any and/or all of the tables in the database to a number of other formats, including CSV and SQL.

Now that we have accessed the never-ending stream of tweets associated with our keywords and location preferences through Phirehose, collected those tweets with the get_tweets method, parsed them into a usable format with the parse_tweets method and exported them from the LAMP server in usable formats (CSV and SQL), the data collection phase has concluded.

Data Analysis

With all captured tweets and metadata parsed into formats compatible with data analysis software, there are several approaches necessary to address the research question. First, I perform content analysis on the text of the tweets themselves to better understand the data and work down to a level where qualitative review is even possible. Second, I use network analysis based on the unique usernames that send and receive communications within the captured tweets. The results identify both prominent usernames and characteristics of the overall network graph for comparison between collection sessions. Finally, once the data is limited by textual and geographic parameters to a human-readable quantity, I perform qualitative analysis as to the validity of any traces that appear clearly linked to real trafficking incidents. Put together, these three separate processes represent logical, repeatable steps that other researchers or analysts might take to discover individual trafficking cases in a massive set of electronic traces.
Content analysis methodologists that I have been exposed to thus far suggest that “proper” use of the method is limited to structure and function and excludes the meaning of that content. I interpret the meaning and implications of the results of this content analysis in my discussion and conclusions, naturally, but the automated and quantitative processes that lead me to those conclusions remain agnostic to the meaning of the captured tweets.

**Preprocessing and Pre-Testing**

The phpMyAdmin software includes an “export” feature. I first exported the “tweets” table from the LAMP server in its entirety. The result was a CSV file that was both incredibly large and filled with characters and patterns that caused my data analysis tools to enter and infinite loop. My solution was to export a single column (tweet_text) that only included the text of each tweet, as the metadata would not be useful for the text mining phase.

The tweet_text column, including tweets from all collection sessions, contained over 3.9 million rows. This caused many, many problems for the tools at my disposal. For example, I needed specialized software just to open the CSV file. Using the text editor Notepad++, I attempted to use the Analyse plugin for basic text mining operations. The file was too large for Analyse, so I looked elsewhere to a text mining program called Hermetic Word Frequency Counter. Using the free trial version of Hermetic, I was able to conduct a very messy pre-test. Hermetic WFC scans the text for unique terms. Every time a new word is encountered (i.e. one that the program has not yet seen in the document), the rest of the text is scanned and the frequency of that term is counted. The program ran for 12 hours before I terminated it due to memory issues. In total, Hermetic WFC retrieved over 500,000 unique words and their frequencies. The test was not complete (I cannot speak to the number of unique terms in the entire dataset without a major hardware upgrade) in several ways: the program never finished...
identifying all unique words in the file, and the trial version of Hermetic WFC obscures parts of the terms and/or their counts in the output file. Regardless, I consider this an important first step as Hermetic WFC was the first and only program capable of actually opening and parsing my dataset in its entirety. With better hardware (namely more RAM) at my disposal, Hermetic WFC would have been capable of finishing the job. The pre-test results are included in Figure 4 below. Terms with frequencies greater than 10,000 were included.

<table>
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<th>Rank</th>
<th>Freq</th>
<th>Word (longest has 50 characters)</th>
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<td>1</td>
<td>254047</td>
<td>old</td>
</tr>
<tr>
<td>2</td>
<td>228182</td>
<td>http</td>
</tr>
<tr>
<td>3</td>
<td>188898</td>
<td>dadd-</td>
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<tr>
<td>4</td>
<td></td>
<td>year</td>
</tr>
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</tr>
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<td>rape</td>
</tr>
<tr>
<td>7</td>
<td>45623</td>
<td>just</td>
</tr>
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<td>8</td>
<td></td>
<td>amp</td>
</tr>
<tr>
<td>9</td>
<td>41111</td>
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</tr>
<tr>
<td>10</td>
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<td>girl</td>
</tr>
<tr>
<td>11</td>
<td>29432</td>
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<tr>
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<tr>
<td>13</td>
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<td>man</td>
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<td>16</td>
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<td>20101</td>
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<tr>
<td>18</td>
<td></td>
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<td>19</td>
<td>19966</td>
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<td>baby</td>
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<tr>
<td>23</td>
<td></td>
<td>toda--</td>
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<tr>
<td>24</td>
<td></td>
<td>day</td>
</tr>
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<td>25</td>
<td></td>
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<td>peop--</td>
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<tr>
<td>27</td>
<td></td>
<td>madame</td>
</tr>
<tr>
<td>28</td>
<td></td>
<td>miss---</td>
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<td>think</td>
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<td>36</td>
<td>13324</td>
<td>madan</td>
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<tr>
<td>37</td>
<td></td>
<td>world</td>
</tr>
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<td>38</td>
<td>12612</td>
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<td>39</td>
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<td>back</td>
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<tr>
<td>40</td>
<td>12048</td>
<td>removed</td>
</tr>
<tr>
<td>41</td>
<td>11629</td>
<td>apartheid</td>
</tr>
<tr>
<td>42</td>
<td>11549</td>
<td>jame--</td>
</tr>
<tr>
<td>43</td>
<td></td>
<td>last</td>
</tr>
<tr>
<td>44</td>
<td>11427</td>
<td>child</td>
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<tr>
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<tr>
<td>46</td>
<td></td>
<td>shit</td>
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<tr>
<td>47</td>
<td>10927</td>
<td>home</td>
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<tr>
<td>48</td>
<td>10879</td>
<td>kidna-</td>
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<tr>
<td>49</td>
<td></td>
<td>boy</td>
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<tr>
<td>50</td>
<td></td>
<td>nigh-</td>
</tr>
<tr>
<td>51</td>
<td>10748</td>
<td>need</td>
</tr>
<tr>
<td>52</td>
<td>10545</td>
<td>fuck</td>
</tr>
<tr>
<td>53</td>
<td>10530</td>
<td>kidnapped</td>
</tr>
<tr>
<td>54</td>
<td>10331</td>
<td>mtvstars</td>
</tr>
</tbody>
</table>

Figure 4: Pre-Test Results
Even when you consider the limitations of the pre-test, the results were an excellent jumping-off point to guide further text mining operations. The original search terms “daddy, rape, year-old, slave, pimp, slavery, madam (and madame, an alternate spelling), kidnap and kidnapped were all present. The most frequent search term, daddy, will become particularly interesting in subsequent text mining operations (what society has done to that word is nothing short of disgusting). We can immediately see the juxtaposition of signal and noise- “mtvstars” and “Winston” (referring to the Florida State QB accused of rape) found their way into our dataset in a big way alongside more potentially-sinister terms. With a rough idea of what was actually in this dataset, it was high time to move on to more sophisticated text mining.

**Text Mining**

This was a critical juncture in the content analysis phase. On the one hand, I had a program that could feasibly parse the entire dataset. On the other hand, the operations were limited by hardware resources and therefore incomplete. Furthermore, the trial version of Hermetic WFC placed significant limits on what I could actually do with the results. Thus, I opted for a sample of the original dataset so that I could maximize the depth of my analysis with the available hardware and software resources.

I settled on R, a popular statistical package that can perform a vast array of text mining operations. The process was seemingly simple: import text into R, clean/preprocess text, structure text in a term-document matrix (TDM), and compute statistics such as term frequency and word associations. The critical step in this process is the creation of a term-document matrix, as the operation is very similar to the process conducted by Hermetic WFC. As “new” words are encountered when R reads the CSV file, the program stops and scans the rest of the file for other
occurrences of that word. As each word is counted, R records the results in a matrix that can subsequently be queried for different types of text analysis.

The sampling of the original dataset involved some trial and error, as I was unable to discern the breaking point of my resources gracefully. I first decided to take only the English-language tweet text for further analysis, but the resulting CSV was too large for R to process in a timely manner (14 hours in, with my machine stretched thin in terms of memory and risking overheating, I terminated the process). The SQL query necessary to take only a sample of rows from the ‘tweets’ table was too complicated for the phpMyAdmin OS to execute, so I had to take even uglier steps to “chop” down the table in a scientifically sound manner.

This “systematic random sampling” of the English-language capture occurred in several steps: starting with the tweet_text column of the original table, I used Excel to assign unique identifiers to each row (a number, starting with ‘1’ for row 1). Next, I used a conditional statement where only rows where the unique identifier was evenly divisible by 5 would print in the following column. The result was a sample dataset containing every 5th tweet (a little over 440,000 rows of text as opposed to 2.2 million).

Using the ‘tm’ (text mining) package in R, I was able to work with the sample dataset within the bounds of my hardware resources. I cleaned the unstructured text through several operations: converting the text to lowercase, removing punctuation and numbers, removing “stop words” such as articles, stripping the whitespace left over after all of the other operations, and “stemming” with the “Snowball” algorithm introduced by Porter. Inspecting the preprocessed document, R enabled me to see that each operation had concluded successfully.

Creating a term-document matrix (TDM) from the preprocessed sample dataset took roughly an hour, leaving enough memory to prepare calculations for the finished TDM. Finding term frequencies, with the leg-work already accomplished by R to create the TDM in the first
place, now took a matter of seconds. I used the findFreqTerms() method, with minimum frequencies ranging from 10-25 at increments of 5.

For word associations, the findAssocs() method allows users to specify both the target TDM and term and set a minimum threshold for association (correlation, in this case). For example, if I wanted a list of words strongly associated with ‘human trafficking’ in the matrix myTDM, I would enter: findAssocs(myTDM, “human trafficking”, .8). Because findAssocs only works for one term at a time, I limit my term associations to only the most frequently-occurring words that are potentially associated with the research question. I repeat the entire process up to this point without stemming, for comparison.

Lastly, I repeat the term frequency and association calculations for term pairs rather than single words. I do this by embedding an n-gram tokenizer (where n=2) within the TermDocumentMatrix() method. From there, both findFreqTerms() and findAssocs() treat term pairs as single elements in the resulting term-document matrix.

**Social Network Analysis**

The network of tweets resulting from a keyword search (our collection method) is often referred to as a “search network.” There are other terms referring to the same thing, but for this project I will consistently use “search network” to describe datasets generated from keyword searches.

Where a great deal of work has examined properties of nodes and edges to glean semantic knowledge about a specific network, we are also interested in the overall network graph metrics that reveal the structure of a given network on Twitter.

Related work in social network analysis has provided a great deal of valuable information about the properties of sub-networks on Twitter. The impact of Twitter conversations on branding
and word-of-mouth advertising, for example, has been validated with social network analysis by Jansen, Zhand, Sobel, and Chowdury in 2009\textsuperscript{lviii}. This supports our use of conversations as units of analysis with Twitter networks as units of observation. The researchers used follower networks, however, and were not interested in the differences in overall graph metrics. Adali, Sisenda, and Magdon-Ismail studied the statistical properties of tweets to predict the nature and structure of social relationships, demonstrating that valuable semantic information can be found in the mathematical properties of nodes and edges in a network graph\textsuperscript{lix}. Again, however, the focus rests with social behavior at an individual level rather than the overall graph structure.

Several other works have detailed the importance of network graphs in gleaning useful information from Twitter networks. Mendoza, Poblete, and Castillo examined the propagation of rumors versus actual news during a 2010 earthquake in Chile\textsuperscript{lx}. Through social network analysis, they discovered that rumors were propagated differently than truths. Specifically, rumors were questioned more often proportionally than affirmed truths. While the graph analysis was again aimed at properties of nodes and edges rather than the entire network, it raises a number of interesting questions about the search networks generated by large-scale events. Their findings hint that different events might spur very different-looking networks, somewhat affirming the motivation for our study.

Additionally, there has been a great deal of investigation into predicting events through the properties of Twitter networks\textsuperscript{lxii lxiii}. In these cases, we see a fantastic opportunity to refine predictions based on the global properties of the networks under examination. Once again, taking a step back (to a high-level analysis) is overlooked in favor of more nuanced investigation.

Lastly, social network analysis research outside of Twitter has noted the impact of overall graph metrics on community formation. Girvan and Newman found that overall centrality measures identify tight-knit sub-networks and suggested that future work might discover other predictive uses for overall graph metrics\textsuperscript{lxiv}. 
I use the graph analysis tool NodeXL to perform graph metric calculations. The tool has embedded functions that describe both specific nodes and edges and the network graph in its entirety. Operationally, that includes: the proportion of total vertices (mentions) to total edges, geodesic distance, graph density, average in-degree, average out-degree, betweenness centrality and closeness centrality. Additionally, identifying individual vertices with high in-degree, out-degree or betweenness centrality can reveal key players in a search network.

The parse_tweets script from 140dev creates a table specifically for tweet “mentions,” or interactions. I exported the ‘source’ and ‘target’ columns from phpMyAdmin, each populated by unique identifiers for each user in the dataset. The resulting CSV file was tailor made for NodeXL, but the file was far too large (anything over 10,000 vertices causes serious performance issues in NodeXL according to the developers). Once again, I used Excel to systematically sample the dataset, taking every 512th tweet and landing with a sample of 5,000 rows/edges (interactions) and 10,000 vertices (users).

Mapping

Finally, I wanted to take advantage of the location features of Twitter’s streaming API. Most tweets are not geotagged, but in a sample this large, a usable number of tweets were bound to include location information. First, taking the entire dataset (rather than isolating the third, location-based collection session), I exported all tweets with non-zero values in the geo_lat and geo_long columns of the ‘tweets’ table. Using the “rworldmap” package in R, I imported the CSV file containing coordinates for every geotagged tweet and plotted those points on a world map. Then, I examined the area of the bounding box specified in the third collection session, with a bit of padding for perspective. Both maps are included in the results section.
After visualizing the geotagged tweets, I reverted to the text mining package in R to gather term frequencies and associations from tweets that fell within the longitude parameters of the bounding box.
Chapter 7
Results

After all three collection sessions, the database contained just over 3.9 million tweets and associated metadata.Parsed into several tables (interactions, users, links, hashtags), I was able to utilize almost all of that metadata in conjunction with the unstructured tweet text to shed some light on my research question.

First and foremost, there was a large disparity in favor of English-language tweets versus transliterated Arabic tweets, given the same amount of time (rounded to the nearest hour) and the same search terms (Table 1). The geotagged count may be slightly exaggerated; as Phirehose freely leaves the bounding box in pursuit of trending topics and tweets relevant to things tweeted inside the bounding box. This is rectified later in the mapping section, where only tweets within the bounding box are plotted and mined.

<table>
<thead>
<tr>
<th>Collection Session</th>
<th>Count</th>
<th>Count/Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>English</td>
<td>2,147,697</td>
<td>536,924.25</td>
</tr>
<tr>
<td>Arabic (transliterated)</td>
<td>180,965</td>
<td>45,241.25</td>
</tr>
<tr>
<td>English (geotagged*)</td>
<td>1,578,623</td>
<td>1,148,089</td>
</tr>
</tbody>
</table>

Table 1: Frequency of Tweets by Language

Text Mining

The findFreqTerms() method returned few terms occurring at even relatively small frequencies, shown in Figure 5. In a sample of over 500,000 rows, 25 occurrences is not a high threshold. Still, given what the pre-test showed us about the entire dataset (“daddy”, for example, appeared over 180,000 times), these results from findFreqTerms() might say more about the sample size or, perhaps, the limitations of my computing resources than the actual data. The most
frequent terms in the sample are consistent with the pre-test, lending a bit of strength to the 
external validity of the systematic random sampling procedure.

```r
> library(tm)
> findFreqTerms(TDM, 10)
[1] "amp" "daddi" "day" "home" "just" "like" "old" "rape" "son" "year"
> findFreqTerms(TDM, 15)
[1] "amp" "daddi" "old" "year"
> findFreqTerms(TDM, 20)
[1] "daddi" "old" "year"
> findFreqTerms(TDM, 25)
[1] "daddi" "old" "year"
```

Figure 5: findFreqTerms() results

Readers will certainly notice the odd spelling of some of the terms (namely “daddi” as opposed to “daddy”). This is a result of the stemming algorithm, and perhaps a necessary evil considering the advantages that stemming provides in combating misspellings and different potential tenses/numbers of interesting terms. The inclusion of only two search terms in these results (“rape” and “daddy”) was initially discouraging, but term frequency is a surface measurement for text mining and the sample was clearly not telling the whole story at this point (compared to, even, the incomplete pre-test).

In addition to the TDM method, R allows the creation of a refined term-document matrix that removes sparse words from the matrix. The original TDM contained 933 unique terms. Refined to strip out sparse words, the TDM contained only 115 unique terms. The term frequency results, shown in Figure 6, were unsurprisingly similar.

```r
> findFreqTerms(TDM_common, 10)
[1] "amp" "daddi" "day" "home" "just" "like" "old" "rape" "son" "year"
> findFreqTerms(TDM_common, 15)
[1] "amp" "daddi" "old" "year"
> findFreqTerms(TDM_common, 20)
[1] "daddi" "old" "year"
> findFreqTerms(TDM_common, 25)
[1] "daddi" "old" "year"
```

Figure 6: findFreqTerms() results for "sparse" TDM

This says good and bad things about the sample. The most frequently-occurring terms were identical in the pre-test, TDM and refined TDM. That means that, with 500,000 unique terms, 933 unique terms and 115 unique terms respectively, the same words found their way to the top of the term frequency ranks. Thus, at least at the top, the sample was consistent with the rest of the dataset. Still, the number of my original search terms appearing frequently in the TDM
is quite small compared to the pre-test. This is where hardware and software limits reared their ugly heads most prominently, as I can only imagine the data that has gone missing due to sampling.

Still, there are two search terms that have found their way into these results. I ran the findAssocs() method on both of them, and the resulting list of strongly associated terms was staggering. Figure 7 shows the list of words associated with “daddy”, stripped of common words (removing “stop words” automatically was not entirely successful). Clearly, even in the sample (relatively small compared to the original dataset), something is afoot.

Term Associations:
"daddi"
abduct
amber
ass
besexymare
bitch
blond
bloodstain
boob
fuckin
girl
girrl
harass
hpe
kionap
macam
masturb
naked
pedophil
porn
prostitut
rape
sex
sextreffick
sexual
slave
slavery
teen
traffick
uncensoredcori
vagina
virgin
whore
xxx

Figure 7: findAssocs() results for “daddi”

The findAssocs() method determines which words are statistically likely to appear alongside a given term, over a threshold that the user specifies. In the cases of both frequently-
occurring search terms ("daddy" and "rape"), I set a very high threshold (the correlation had to be at least 0.8). That being said, findAssocs() was an excellent means for separating signal from noise within terms that could go either way. “Daddy,” in many cases, was used innocently. However, as we can see based on the list of terms in Figure 7, it was also used nefariously, even in the sample. Figure 8 shows the results of findAssocs() for the search term “rape.”

<table>
<thead>
<tr>
<th>Term Associations:</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;rape&quot;</td>
</tr>
<tr>
<td>abduct</td>
</tr>
<tr>
<td>aballmarkintim</td>
</tr>
<tr>
<td>amber</td>
</tr>
<tr>
<td>anon</td>
</tr>
<tr>
<td>beshexymare</td>
</tr>
<tr>
<td>bitch</td>
</tr>
<tr>
<td>blond</td>
</tr>
<tr>
<td>bloodstainlan</td>
</tr>
<tr>
<td>boob</td>
</tr>
<tr>
<td>bonding</td>
</tr>
<tr>
<td>bust</td>
</tr>
<tr>
<td>child</td>
</tr>
<tr>
<td>daddi</td>
</tr>
<tr>
<td>daddy</td>
</tr>
<tr>
<td>daddygift</td>
</tr>
<tr>
<td>daddymommi</td>
</tr>
<tr>
<td>daddyscrub</td>
</tr>
<tr>
<td>despe</td>
</tr>
<tr>
<td>drug</td>
</tr>
<tr>
<td>enter</td>
</tr>
<tr>
<td>femal</td>
</tr>
<tr>
<td>fuckin</td>
</tr>
<tr>
<td>game</td>
</tr>
<tr>
<td>girl</td>
</tr>
<tr>
<td>grab</td>
</tr>
<tr>
<td>kidnap</td>
</tr>
<tr>
<td>location</td>
</tr>
<tr>
<td>madam</td>
</tr>
<tr>
<td>masturb</td>
</tr>
<tr>
<td>nagpunta</td>
</tr>
<tr>
<td>naked</td>
</tr>
<tr>
<td>pedophil</td>
</tr>
<tr>
<td>pimp</td>
</tr>
<tr>
<td>porn</td>
</tr>
<tr>
<td>pound</td>
</tr>
<tr>
<td>prostitut</td>
</tr>
<tr>
<td>sex</td>
</tr>
<tr>
<td>sextraffick</td>
</tr>
<tr>
<td>sexual</td>
</tr>
<tr>
<td>slave</td>
</tr>
<tr>
<td>teen</td>
</tr>
<tr>
<td>traffick</td>
</tr>
<tr>
<td>vagina</td>
</tr>
<tr>
<td>virgin</td>
</tr>
<tr>
<td>whore</td>
</tr>
<tr>
<td>xxx</td>
</tr>
<tr>
<td>youngin</td>
</tr>
</tbody>
</table>

Figure 8: findAssocs() results for "rape"
One could easily argue that these results generate more questions than answers. I am inclined to agree. At this point, I have reached the logical limitations of quantitative text mining (with R, at least). Generating, for example, clusters of associated terms would take me back to this point. There are other algorithmic ways of “reading” text, such as n-gram tokenization, but ultimately I would be left with statistical associations between words and phrases. In order to find any actual evidence of trafficking, I needed to use my eyes.

Using the Analyse plugin for the Notepad++ text editor, I searched manually for co-occurrences of original search terms.

**Social Network Analysis**

The results of NodeXL’s network graph analysis once again echo the perils of sampling due to hardware and software limitations. In this case, it was the software that did the most damage. MS Excel is limited to just over 1 million rows in a single spreadsheet, but the NodeXL plugin faces even more stringent limits (5,000 lines, 10,000 vertices). Where the text mining sample was reflective of the pre-test in many ways, it is difficult to make any arguments about the external validity of the network analysis sample.

Ultimately, there were 8926 unique vertices in the network graph with 4988 unique edges between them. The disparity between this and the actual number of lines comes as a result of users appearing in the left (source) column multiple times. The maximum geodesic distance (number of “hops” to go from one end of the graph to another) was 3, with an average of 1.09. This is a fairly dense graph with a high proportion of edges to possible edges. That can be explained because, from the tweet_mentions table, we are only looking at tweets with interactions. Graph metrics, in this case, can only speak to how interactive the network was.
compared to how active it could have been. Table 2 details the first “wave” of descriptive graph metrics.

<table>
<thead>
<tr>
<th>Graph Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graph Type</td>
<td>Directed</td>
</tr>
<tr>
<td>Vertices</td>
<td>8925</td>
</tr>
<tr>
<td>Unique Edges</td>
<td>4988</td>
</tr>
<tr>
<td>Edges With Duplicates</td>
<td>10</td>
</tr>
<tr>
<td>Total Edges</td>
<td>4998</td>
</tr>
<tr>
<td>Self-Loops</td>
<td>196</td>
</tr>
<tr>
<td>Reciprocated Vertex Pair Ratio</td>
<td>0.000625782</td>
</tr>
<tr>
<td>Reciprocated Edge Ratio</td>
<td>0.001250782</td>
</tr>
<tr>
<td>Connected Components</td>
<td>4152</td>
</tr>
<tr>
<td>Single-Vertex Connected Components</td>
<td>192</td>
</tr>
<tr>
<td>Maximum Vertices in a Connected Component</td>
<td>64</td>
</tr>
<tr>
<td>Maximum Edges in a Connected Component</td>
<td>63</td>
</tr>
<tr>
<td>Maximum Geodesic Distance (Diameter)</td>
<td>3</td>
</tr>
<tr>
<td>Average Geodesic Distance</td>
<td>1.090155</td>
</tr>
<tr>
<td>Graph Density</td>
<td>6.0215E-05</td>
</tr>
</tbody>
</table>

Table 2: SNA Results (overall graph metrics)

Centrality measures are probably the most telling feature of a given network graph. Here, we cannot tell much from in-degree and out-degree measures. That the maximum in-degree reaches only 63 in a network of almost 5,000 interactions is discouraging. The average betweenness centrality reaching 1.3 is even more discouraging- on average, in the sample network a given user was likely only the “bridge” for 1.3 interactions. These measurements, and other associated measures of centrality, are arranged in Table 3 below.
<table>
<thead>
<tr>
<th>Minimum In-Degree</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum In-Degree</td>
<td>6 3</td>
</tr>
<tr>
<td>Average In-Degree</td>
<td>0 .559</td>
</tr>
<tr>
<td>Median In-Degree</td>
<td>0 .000</td>
</tr>
<tr>
<td>Minimum Out-Degree</td>
<td>0</td>
</tr>
<tr>
<td>Maximum Out-Degree</td>
<td>4</td>
</tr>
<tr>
<td>Average Out-Degree</td>
<td>0 .559</td>
</tr>
<tr>
<td>Median Out-Degree</td>
<td>1 .000</td>
</tr>
<tr>
<td>Minimum Betweenness Centrality</td>
<td>0</td>
</tr>
<tr>
<td>Maximum Betweenness Centrality</td>
<td>3 906.000</td>
</tr>
<tr>
<td>Average Betweenness Centrality</td>
<td>1 .305</td>
</tr>
<tr>
<td>Median Betweenness Centrality</td>
<td>0 .000</td>
</tr>
<tr>
<td>Minimum Closeness Centrality</td>
<td>0</td>
</tr>
<tr>
<td>Maximum Closeness Centrality</td>
<td>1 .000</td>
</tr>
<tr>
<td>Average Closeness Centrality</td>
<td>0 .847</td>
</tr>
<tr>
<td>Median Closeness Centrality</td>
<td>1 .000</td>
</tr>
</tbody>
</table>

Table 3: SNA Results (degree and centrality metrics)

There are three vertices in the sample with betweenness centrality measures greater than 1000. These are significantly high measurements, especially in a sample that is otherwise lacking rich interactions. The unique identifier in the tweet_mentions table is numeric, so I had to reach back into phpMyAdmin with an SQL query to discover the username associated with each numeric identifier. The three handles with betweenness centrality measures greater than 1,000 were: @Nialloficial, @williedevine and @uberfacts. They are, in order: a member of One Direction, a friend of a member of One Direction and a parody account listing useless facts. Not
exactly the movers and shakers I was hoping for, though I do find it odd that they found their way into a dataset populated by human trafficking-related search terms. Expanding my search to users with a betweenness centrality of at least 100, I found one account (@IsaAbdullah91) out of 12 that had any apparent interest in my research question. The account had a modest following (just over 700 users) and appears to tweets about several international affairs topics (Syria included). For perspective, I present the sample network graph in two forms: in Figure 9, the pop culture icons and parody accounts are highlighted, whereas @IsaAbdullah91 is highlighted in Figure 10. Needless to say, this was either a disappointing set of interactions or a bad sample (or, perhaps, both). Still, as a proof-of-concept, I have demonstrated that it is possible to identify critical nodes in a search network and quickly put faces to numeric identifiers.

Figure 9: Network Graph with most frequent nodes highlighted
Mapping, Location-Based Text Mining

Finally, I attempted to tie the dataset to the Syrian case geographically. Nothing in either of the previous analytical methods indicated electronic traces that functionally tied to the human trafficking situation among refugees, so my hope was to focus collections on the area itself. The rationale was that primary sources might not include the name of their location, especially in English, in their posts. While that proved to be true, at least as far as the sample shows, there were tweets coming from inside my geographic area of interest.

While most tweets are not geotagged, even a small percentage (~2%) would offer a large dataset given the 3.9M total captured. In all collections, 148,561 tweets fell within the longitudinal boundaries set by the third collection session. Across all captures, 806,424 tweets included lat/long coordinates. The third collection session (which was supposedly limited to my
bounding box) totaled over 1.5M results, so this sheds some light on just how liberal Phirehose can be when it comes to interpreting location boundaries.

The location-based tweets are plotted on a world map in Figure 11. We can see the activity consistent with more-populated areas, sans parts of the world that either lack connectivity or places where Weibo is the dominant microblogging tool (i.e. East Asia). Still, the objective here is to tie these terms and, more generally, collection methods to our bounding box (Syria, with padding). Tweets geotagged within the bounding box, including tweets originating from inside Syria, are plotted in Figure 12 below.

Figure 11: Mapping results (global)
After plotting the geotagged tweets to discern \textit{where} this (albeit small) cut of users hail from, I wanted to compare the \textit{content} of their tweets versus the content of the first collection session. Re-tracing my steps through the text mining package in R, I created a term-document matrix from the text of all geotagged tweets (70 unique terms). The results of the \texttt{findFreqTerms()} method are presented in Figure 13. The only original search term appearing here is “madam,” and it only appears twice. In fact, this TDM is almost entirely sparse- no terms appear 5 or more times within my geographic bounding box. For the sake of completeness, I ran the \texttt{findAssocs()} method on “madam” within the geotagged TDM. The results, not surprisingly, were blank, even at very low association thresholds (down to 0.6).
Chapter 8
Discussion

Before I begin interpreting results, readers should be aware of potential pitfalls associated with the study. First and foremost, the sampling methods were neither truly random nor perfectly representative of the data. While tweets were systematically selected without discrimination (every 5\textsuperscript{th} tweet was chosen; this was merely done to “fit” into computational limits), tweets were taken from a table where they were ordered chronologically. I do not see this as a detriment to validity because the selection showed no preference to the structure or function of tweets, and structure and function were the targets of my analyses. Still, it is disappointing to lose so much potentially valuable data and there is no statistically solid method for comparing this sample text to the overall corpus that was originally collected without tools that can analyze the original corpus. Of course, having those tools would also make sampling a moot point and would greatly enhance the internal validity of each analysis within the study.

Moreover, the term-document matrix rightly seems like a limited method for text processing. The subsequent methods (findFreqTerms and findAssocs) are based entirely on term frequency and adjacency to other like terms. This means that slight variations in characters, including spelling errors and changes in tense or number, constitute new unique characters in the term-document matrix. Stemming can combat this, to an extent, but spelling mistakes are so common on Twitter that the TDM might be problematic even after accounting for the “damage” done by sampling. With and without stemming, it is very likely that the term-document matrix methods either ignored or misplaced terms due to small variations in characters and, therefore, the internal consistency of frequency and association methods in R’s text mining (“tm”) package is not ironclad.
Solving the above sampling and term selection problems would still not account for language barriers. I have already discussed the weakness of the internal link between this data and the Syrian case, and the absence of Arabic search parameters likely played a role in said weakness. Transliteration does not, by any means, amount to translation. Moreover, there are many dialects of Arabic that are regionally, or even locally, diverse. If there were tweets that met our specifications both functionally and geographically, it seems more likely that we would stumble onto them in a native language than in English. Transliterated Arabic, while not entirely absent over the collection phase, appears much less frequently than I anticipated, but it would be naïve to make assumptions about the quantity and/or content of Arabic-language tweets based on the transliterated collection. This likely takes a toll on external validity, as the corpus of tweets (especially the sample) may not be representative of what actually exists “in the wild” concerning both human trafficking and the Syrian case. On a more positive note, I only counted the transliterated Arabic tweets. Applying even the simple text mining methods used in this study to that body of electronic traces might yield more interesting results (or nothing at all). Specifically, some of the more targeted search parameters (for example, a slang term for arranged marriage) might appear in this collection despite their absence in the English text.

The final and perhaps most significant contributor to this list of potential pitfalls effecting the results is the selection of Twitter as a source of electronic traces. Based on the literature review, Twitter did not appear to be the ideal selection for investigating traffickers, let alone in this very specific context. Twitter is very much a public forum and thus likely not as appealing to traffickers as, for example, online classifieds (where they are less identifiable) or the “dark web.” Twitter does provide options for users to “protect” their tweets, but this makes it more difficult to reach audiences. Moreover, automated data collections (such as this one) would not reach protected tweets. Also, while there is an active Syrian Diaspora on Twitter, it may have been ambitious to assume that human trafficking cases among Syrian refugees would surface in the
conversation (or, perhaps, that conversation was simply not happening in English). As far as linking victims or those close to victims to specific electronic traces, it is highly likely that they do not have either internet access or smartphones, though the cause is difficult to determine without more evidence. Again, the internal link between *these* Twitter posts and displaced Syrians is weak, and the very selection of Twitter as a platform for data collection may have contributed to both this and the aforementioned pitfalls.

From a technical standpoint, collection and analysis progressed smoothly once I accounted for hardware and software limitations. As far as I can tell, Phirehose returned an exhaustive list of results within the specified search parameters. Moreover, the number of collected tweets matched the number of parsed tweets, meaning there were not missing data left unsorted on the LAMP server. The “export” tool in phpMyAdmin did not lose rows in the conversion to .csv. Lastly, the text mining results were roughly consistent with the pre-test, leading me to believe that the text mining functions in R were operating as advertised.

Looking in the wrong places with the wrong search parameters is a human error, so the system was syntactically sound. In spite of internal and external validity issues caused by the human-in-the-loop during this particular study, the collection and analysis tools operated with excellent internal consistency. This repeatability does not prove my concept or even answer my research question, but it does provide a foundation for future work based on these ideas.
Chapter 9
Conclusions

There is no evidence of human trafficking among Syrian refugees in this study. The data may have more to say upon an exhaustive examination, but this study did not unearth anything remotely incriminating. Thus, as a proof-of-concept, the only proof is that this execution was unsuccessful. However, returning to the research question, these results are neither damning nor reassuring for the concept under scrutiny. It is still entirely possible that the collection and analysis of electronic traces in social media could augment existing monitoring practices for human trafficking among displaced persons. It is even possible that text mining, social network analysis and mapping of Twitter data could augment those practices. The lack of results in this study was less reflective of the collection and analysis tools than of the approach taken to the search for evidence.

In fact, the lack of results in this study sheds a great deal of light on the concepts under investigation and offers plenty of guidance for future research. Starting with human trafficking, these results lend evidence to the possibility that many traffickers avoid Twitter in favor of other online services. The public nature of Twitter (and Facebook, for that matter) might be a logical deterrent for someone looking to make illicit transactions or even advertise illicit “products” in a way that could lead back to them. Online classifieds, ample in other studies about online human trafficking, might provide a kind of anonymity that many social media platforms simply do not offer. Everyday users have complaints with the privacy policies on social media sites, and their livelihood likely does not depend on using those sites undetected. Moreover, if traffickers are using Twitter, the search parameters in this study were unfit for discovering the perpetrators.

First, the focus on English-language posts was likely damaging the prospect of discovering human trafficking evidence from the beginning. In another case study, perhaps one geographically sighted to a place where English is the dominant language, this might have been a
more fruitful strategy. In Syria and the immediate surrounding areas, English social media posts are probably rare among natives. The concentrations of English-language tweets within my bounding box correlate with refugee camps and lead me to believe that aid workers and other English-speaking volunteers were responsible. Traffickers and their victims, if those victims are displaced Syrians, probably are not speaking English, let alone speaking English on Twitter.

Lastly, the list of search terms probably came up short in several regards. Some of the terms were far too general, returning heaps of results that amounted to nothing but noise. Other terms, though more targeted, were not likely to appear in English (or, perhaps, the exact way that I spelled them out). Using flawed terms in the wrong language on the wrong platform for data collection accounts for 99% of the aforementioned issues. That is disappointing for this particular study, but offers an excellent example of what not to pursue in future work.

There are also lessons about the Syrian case, some of which might be extensible to other case studies about human trafficking in specific contexts. The geolocated tweets took on a character of their own, revealing something about the crisis both spatially and functionally. First, the vast majority of tweets inside the bounding box across all languages came from refugee camps. Inside Syria, the results were dispersed too much to make sense of, which is interesting in itself (we might expect concentrations in urban areas, for example). The majority of displaced Syrians are displaced internally, meaning that the majority of Syrians are not using Twitter. Also, the plurality of Syrian refugees resides in Lebanon, where there are no official refugee camps. Further investigation is necessary to determine the structure of function of Tweets in this dataset originating from Lebanon, but a quick look at the mapping results shows a blank space along the Syria-Lebanon border. That is counterintuitive given the frequent and heavy traffic of refugees and fighters moving through that region. While these issues do not excuse the lack of results, they open up the possibility that more refined executions of my concept might return more interesting results.
Lessons about human trafficking (generally speaking) and the Syrian crisis aside, the weak internal link between human trafficking and displaced Syrians in this study is discouraging. Perhaps this merely highlights the vulnerability of such populations to traffickers and the immense difficulties faced by researchers, aid workers and law enforcement in monitoring human trafficking in this context. Throughout the course of this study, reports of trafficking incidents and survival stories from victims did not subside, but my execution in this study was unable to speak to those incidents. That should not discourage future attempts, however, as there is a great deal of room for improvement on these methods and concepts.

The collection and analysis methods were operationally sound. Given several iterations with different collections of text, the text mining package in R returned consistent results. There are probably far more sophisticated natural language processing and text mining tools available for a price, but the cost (zero) and customizability of R makes it an attractive option for future work. NodeXL is a vastly limited social network analysis tool, but there are other open source options that I was not familiar with before this study that might open doors to better results. The concept of using network graph metrics to understand huge datasets, however, has a place in augmenting existing monitoring methods. The same can be said for mapping. Given more targeted inputs, this “system” for making sense of massive amounts of social media data has a great deal of potential.

Most importantly, this study makes profound statements about the logical approach to big data projects. The temptation was to cast a wide net and use analytical methods to narrow results until something interesting surfaced. The problem with that approach, in the case of human trafficking among Syrian refugees, is that analytical methods for unstructured text are probably not good enough in practice to narrow the field down to what I am looking for. Even if they were, it may be more sensible and more efficient to cast a smaller net or even start in the “weeds.” For example, I might have begun with an account of a specific trafficking incident and cast a net
solely over that incident. Then, using that new information (such as the location and methods of traffickers in that incident), I might use very specific search parameters in the wild and find a similar but unreported incident. Even with a massive dataset, approaching a research question from specific cases and branching out into the rest of the data has unexplored potential, at least in the context of human trafficking.

These conclusions do not, of course, satisfy the research question. The question of whether electronic traces in social media can augment monitoring practices for human trafficking, even narrowed to the context of displaced persons, is far too large to answer in one small step. Still, this study sheds a bit of light on human traffickers and the Syrian crisis that might be useful for researchers going forward. As for this case, there is a shroud over traffickers among displaced Syrians that I was not able to permeate, but better execution taking into account the lessons learned in this study may unearth primary evidence.
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