A machine learning approach to scenario analysis and forecasting of mixed migration

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The development of MM4SIGHT, a machine learning system that enables annual forecasts of mixed-migration flows, is presented. Mixed migration refers to cross-border movements of people that are motivated by a multiplicity of factors to move including refugees fleeing persecution and conflict, victims of trafficking, and people seeking better lives and opportunity. Such populations have a range of legal status, some of which are not reflected in official government statistics. The system combines institutional estimates of migration along with in-person monitoring surveys to establish a migration volume baseline. The surveys reveal clusters of migratory drivers of populations on the move. Given macrolevel indicators that reflect migratory drivers found in the surveys, we develop an ensemble model to determine the volume of migration between source and host country along with uncertainty bounds. Using more than 80 macroindicators, we present results from a case study of migratory flows from Ethiopia to six countries. Our evaluations show error rates for annual forecasts to be within a few thousand persons per year for most destinations.

Introduction

Currently, more than 68 million people are forcibly displaced worldwide, the highest figure in recorded history. Among them, 25.4 million are refugees, half of whom are under the age of 18 [1], while a further 232 million migrants live outside their country of birth. High levels of displacement have had broad socio-economic impact and have led to a divided polity. To address these issues, governments from across the world came together to adopt a pact to improve cooperation on international migration. Among other objectives, the Global Compact for Migration [2] seeks to use "accurate and disaggregated data as a basis for evidence-based policies."

Understanding migration dynamics and drivers is inherently complex. At the individual level, circumstances differ from person to person. The question, "Why did you decide to move?" is not straightforward for people to answer. At broader levels, quantitative measures of migration are often sparse and limited. Various jurisdictions differ in their criteria, resulting in disparate measurements. Some categories of migration are inadequately tracked in such statistics, for instance irregular migration.

In this article, we describe MM4SIGHT, a machine learning system to provide forecasts of mixed migration. Mixed migration is defined as cross-border movements of people that are motivated to move by a multiplicity of factors, including refugees fleeing persecution and conflict, victims of trafficking, and migrants seeking better lives and opportunity. Such forecasts are important for informed, data-driven policy development and decision making and creating proactive programmatic response.

The system leverages in-depth interviews of thousands of refugees and migrants on the move conducted by the Mixed Migration Centre (MMC), which is part of the Danish Refugee Council (DRC) under its Mixed Migration Monitoring Mechanism Initiative (4Mi) to assess, among many other issues, their motivations to move. The main drivers are categorized into several broad clusters that are then mapped to aggregate measures capturing various aspects of societal wellbeing. An ensemble model is then

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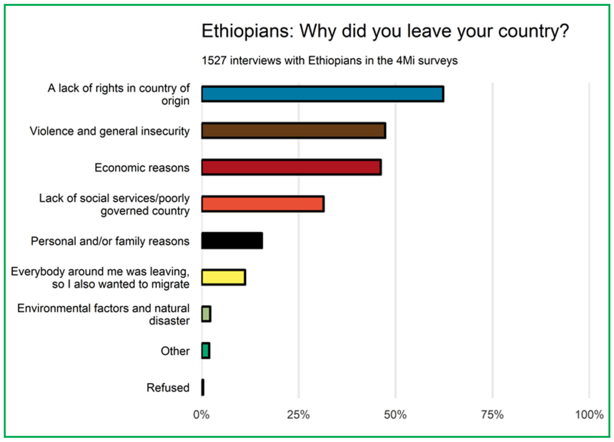

Figure 1

Driver categories from 4MI ($n = 1527$).

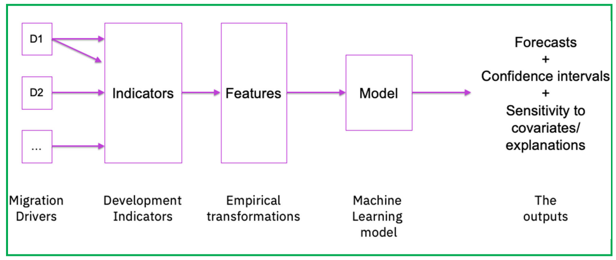

Figure 2

Overall pipeline of MM4Sight.

used to make forecasts of bilateral country volume of migration. The base forecasts assume "as-is," existing conditions. The models are sensitive to changes in underlying factors to enable scenario forecasts, i.e., revised forecasts when any combination of socio-economic indicators changes.

This article outlines the approach and demonstrates results for a pilot implementation to forecast mixed-migration flows from Ethiopia to six destination countries.

Approach

Migration begins with a person deciding to move. Individual circumstances around such a decision are unique. Aspirations to relocate may be latent for a long period before means to do so are available, or until conditions sufficiently deteriorate making movement unavoidable. Understanding migration dynamics is, therefore, inherently complex. To the extent that individual decisions reflect structural societal factors, we seek to partially explain migratory flows by aggregate measures. For instance, economic drivers of migration can be expected to be related to lack of employment opportunities and, therefore, aggregate employment rates in a region.

Which aggregate factors should one consider? To address this question, we leverage data from the 4Mi program [3]. Established in 2014, 4MI conducts in-depth surveys with thousands of refugees and migrants on the move, collecting approximately 1,000–1,200 surveys each month. Analysis of survey data reveals high-level clusters of drivers for migration as shown in **Figure 1**. These clusters ranged from lack of rights and other social services, to economic necessity and conflict. These drivers are then mapped to quantitative indicators.

From a range of institutional data providers (e.g., World Bank, UNHCR), we gather a comprehensive set of development indicators such that a broad scope of migratory drivers is represented in the model. These include statistics on the labor economy, food, education, socio-demographics, infrastructure, strength of institutions, and governance.

An ensemble model is trained from these indicators and historical data on migration. Since data coverage is sparse, both for the target variable of different migration categories and indicator variables, we leverage data from other Sub-Saharan countries, where the relationships between the drivers and migration would be consistent. A trained model can then be deployed to generate point forecasts. Uncertainty around point forecasts is generated using a quantile regressor using the same feature set. This overall system pipeline is illustrated in **Figure 2**.

Formally, we have a set of regions (typically countries) indexed by i, j for which we seek to predict migration volumes $y_{ij}(t+n)$ between region i and j at time $t+n$. Based on historical data on migration volumes, indicators at source, and destination countries, we seek to establish the relationship

$$y_{ij}(t+n) = f\big(y_{ij}(t), X_i(t), X_j(t)\big)$$

where $f(.)$ is the ensemble model learned from historical data, and $X_i(t)$ are the set of macroindicators for geography i. The macroindicators can additionally include lagged indicators, i.e., $X_i(t-m)$, such that longer term impacts of specific indicators and their impact on migration can be captured.

Such a model can generate "as-is" forecasts—forecasts in which existing conditions remain unchanged—for bilateral migration volumes. Bilateral migration volumes are the number of persons migrating between two countries. To model bilateral migration under a new (unobserved) scenario, the model accepts revised macroindicators to regenerate a forecast. These are "what-if" scenarios. For a specific scenario to be supported by observations, additional considerations are necessary to address two problems.

First, to address data sparsity, i.e., the limited number of observations on which the model is trained, we consider data from other countries in the training set region. While the model is employed for bilateral flows from Ethiopia, we

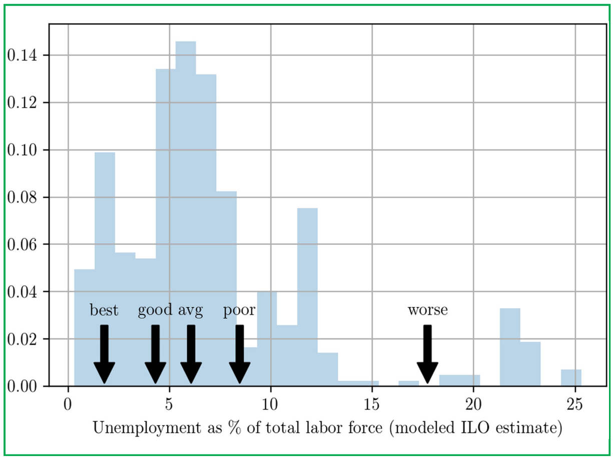

Figure 3

Example of mapping user scenario specification to feature quantiles. Unemployment rates for Sub-Saharan countries between 1990 and 2015 ($n = 518$).

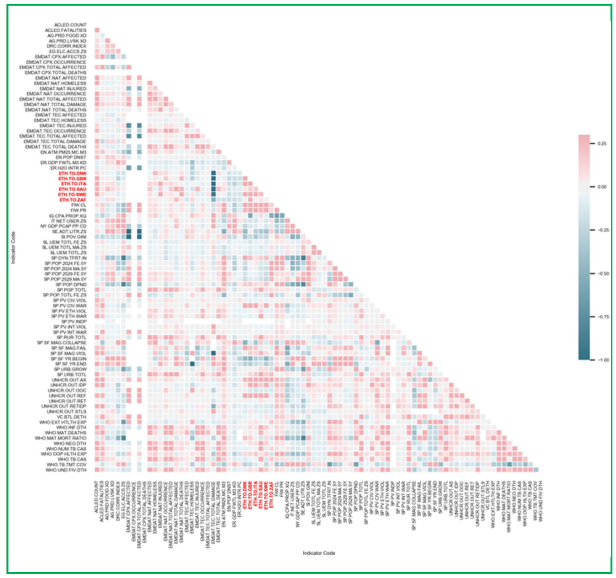

Figure 4

Cross-correlation plot between considered macroindicators and targets for each year without considering temporal effects.

consider data for most Sub-Saharan countries. The underlying assumption is that the statistical relationships between socio-economic indicators and migration is roughly similar. This assumption does not aim to correlate volatility in flows or volumes across countries.

Second, we limit scenarios to those that have been observed for any of the Sub-Saharan countries in the past. To do this, we estimate quantiles for each feature used in the model and assign the median value to a user-oriented five-point scale: worse, poor, average, good, and best. A sample for unemployment rates is illustrated in **Figure 3**.

Features are categorized by theme and subtheme to allow for scenario models that are easy for end users to build. Each cluster consists of multiple features. Users interact with the system by changing the quantile labels (e.g., "poor" → "good"), and the system maps the empirical quantile transformations to generate a revised forecast. The set of themes includes public health, food security, employment, infrastructure, and conflict.

Modeling scenarios ensure that the forecasts are within observed ranges for indicators and can be interpreted directly. However, the approach is not without limitations. For features that are not adequately normalized, median values may be skewed by a few large values. For such cases, indicator values must be appropriately normalized so that a scenario specification translates to reasonable jumps in underlying feature values. For example, in Figure 3, unemployment rates must more than double when conditions are considered to go from "poor" to "worse."

Implementation

The target forecast variable is bilateral mixed-migration flows. However, by nature of encompassing different groups of people on the move with different legal statuses and moving via different means (both regularly and irregular), there is not one database available with "people on the move in mixed-migration flows." We reconstructed those populations from several sources. First, we interpolated net migration figures from the United Nations Department of Economic and Social Affairs (UNDESA), which include economic migrants and refugee counts for some regions. Then, we consider United Nations High Commissioner for Refugees (UNHCR) estimates of refugees, asylum seekers, others of concern, and returnees. Finally, we include DRC survey estimates that comprise unofficial counts of migrants on the move, particularly to Saudi Arabia.

We then focused on assembling macroindicators that reflect drivers uncovered by 4MI surveys. Using several institutional data providers, such as the World Bank and the UN agencies, we assembled 85 indicators that mapped to various aspects of socio-economic welfare. **Figure 4** illustrates a correlation plot between considered features and targets.

The data assembled was global in scope. However, for a more precise evaluation of the system, we focused on Ethiopia and migration patterns to six destination countries. For validation, the system was trained on data from 1995 to 2010 and tested on a period of 2011–2016 for one-year-ahead forecasts.

We experimented with several variants of feature sets. Spatially, we tested for data on Ethiopia alone and then for a dataset augmented with 21 other countries from

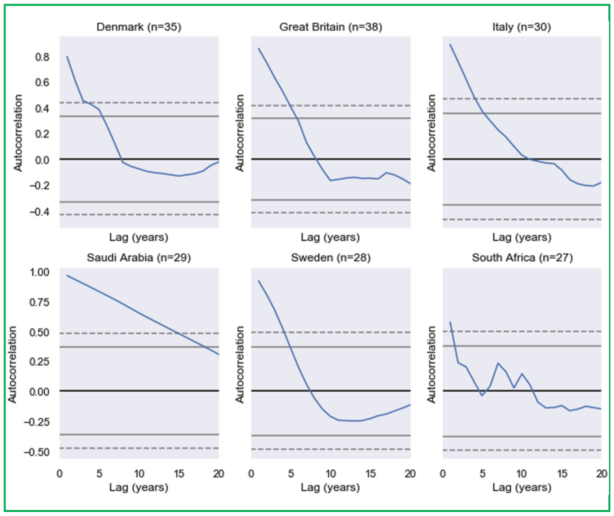

Figure 5

Autocorrelation plots for bilateral flows showing high correlation for year-to-year migration.

Sub-Saharan Africa. The augmented case assumes statistical relationships between socio-economic indicators and migration volumes are roughly similar across countries. We considered temporal lag features, those that potentially have a delayed impact on migration. Finally, since direction and volume of migration flows are not only determined by indicators in the country of origin, but also by indicators in the country of destination (e.g., demand for labor, visa regulations, etc.), we considered features for destination countries as well.

Temporally, we tested the inclusion of autoregressive features, i.e., previous years' flows. As shown in **Figure 5**, there is a high correlation across years. We also tested inclusion of lagged features for covariates by performing cross-correlation analysis. These features lacked the impact of migration drivers. For example, conflict-induced displacement may be more immediate than movement due to lack of services. We employed standard techniques for scaling and hyper parameter tuning.

We tested four model classes: a gradient boosting ensemble (xgboost), random forest, a linear regression, and a support vector regression. The baseline was considered to be the previous year's value, i.e., flows at year n are considered as forecasts for year $n + 1$. The baseline is very competitive for most country pairs evaluated as shown in Figure 5.

In addition to the point forecast, a quantile regressor was trained to create a one-sided 95% confidence interval. For this, an xgboost model with a quantile loss function was employed.

We used two validation measures to evaluate the feature/model combinations: mean absolute error (MAE) and mean absolute percentage error (MAPE). We selected a feature model specification to be consistent across model classes. Results are shown in **Table 1**.

While the mean error was $\sim$6,000 persons, there is variability in forecast quality across destinations. The scale of flows also varies considerably. Flows to Saudi Arabia during the test period were highly volatile (50–150 K). In this case, the model generated two missed forecasts during the validation period. The model also missed one forecast to South Africa, where there appears to be an abrupt reduction in migration volumes in 2016.

This model was then deployed to generate forecasts for 2018, where it estimated $\sim$84,260 persons to move to Saudi Arabia, $\sim$35,950 persons to South Africa, and a total of $\sim$8,000 persons to the four European countries (Denmark, Great Britain, Italy, and Sweden).

Based on official statistics for Sweden and Denmark available for the first three quarters of 2018, we estimate a projection error of $\sim$700 persons and $\sim$600 persons to Sweden and Denmark, respectively. International Organization for Migration (IOM) estimates for Ethiopian migration to Saudi Arabia in 2018 is estimated at 138,000 persons, suggesting a missed forecast.

We further analyzed scenario forecasts for 2018 under a range of conditions. Since we consider the model for all Sub-Saharan countries, we present selected scenarios as relative to this cohort of countries based on a five-point scale for the region. Relative changes in migration volumes are summarized in **Table 2**. It is important to note that these are statistical relationships. No causal relationships can be inferred from the model.

Health: Current health infrastructure in Ethiopia is in the bottom fifth percentile in Sub-Saharan Africa for several indicators. If health infrastructure were to improve to the best fifth quantile (relative to Sub-Saharan countries), migration is likely to decrease to South Africa by approximately 23% and to Saudi Arabia by 11%. Movements to the other destinations are forecasted to increase by $\sim$30%.

Economy: Unemployment rates in Ethiopia are above average compared to Sub-Saharan countries. Increases in employment rates to the best fifth will result in reduced migration to Saudi Arabia and Italy. Increases in unemployment rates are not forecasted to have significant change for other selected destination countries.

Conflict: Conflict indicators are among the bottom fifth in the region. If the conflict conditions improve, migration flows to Denmark and Sweden are expected to reduce by 29% and 18%, respectively.

Related work

Several quantitative migration models have been presented in the literature, starting from the Ravenstein's laws of migration, to gravity models and push–pull frameworks to assess flow patterns.

Table 1 Summary of validation error metrics MAE and MAPE for chosen model: Gradient boosted tree models with data for Sub-Saharan countries, autoregressive features, and lag variables based on seven annual forecasts for 2011–2017.

From Ethiopia to:	MAE	MAPE	# Missed Forecasts	Without missed forecasts	
				MAE	MAPE
Denmark	26	13.4%	0	26	13.4%
Great Britain	560	32.5%	0	560	32.5%
Italy	602	28.4%	0	602	28.4%
Saudi Arabia	23293	27.9%	2	15427	18.9%
Sweden	480	17.6%	0	481	17.6%
South Africa	9376	43.5%	1	3480	35.7%

A missed forecast is instances where the forecast error was larger than 40,000 persons per year.

Table 2 Scenario projections for 2018 for selected thematic clusters.

	Health					food security				
destination	worse	poor	avg	good	best	worse	poor	avg	good	best
Denmark	Current	o	o	o	o	o	o	o	o	Current
Great Britain		++	++	+++	+++	+++	+++	+++	+++	
Italy		+++	+++	+++	+++	--	--	--	--	
Saudi Arabia		-	--	--	--	o	o	o	o	
Sweden		--	--	++	++	++	++	++	++	
South Africa		o	--	--	--	--	--	--	--	

	employment					infrastructure					conflict				
destination	worse	poor	avg	good	best	worse	poor	avg	good	best	worse	poor	avg	good	best
Denmark	o	o	o	Current	o	o	o	o	o	Current	Current	--	--	--	-
Great Britain	o	o	o		o	++	++	+++	+++			o	o	o	o
Italy	---	---	++		---	+++	+++	+++	+++			o	o	o	o
Saudi Arabia	o	o	o		--	-	o	o	o			o	o	o	o
Sweden	-	--	o		o	o	o	o	o			--	--	--	--
South Africa	o	o	o		o	-	-	-	o			o	o	o	o

The five-point scale is relative to data from Sub-Saharan countries. Changes in migration volumes are shown to increase (+), decrease (−), or no substantive change (o).

Forecasting of migration has also received significant attention that can be viewed broadly in two categories. Short-term forecasts aimed at operational response in the order of weeks and a few months are aimed at appropriate humanitarian response, while longer term forecasts, as those presented here, are useful for policy setting and prioritization.

In [5], the authors provide short-term forecasts (two weeks ahead) for movements based on traditional indicators (e.g., socio-demographics) and social media sources such as news, Twitter, and event data. They derive roughly 400 features and use a hierarchical Bayesian model to provide probability densities, as opposed to a point forecast. Their evaluation for a case study in Iraq appears to show that nontraditional sources do not improve forecast accuracy significantly. Operational forecasts using time series forecasting methods have been also proposed by the UNHCR [6]. In [4], a multiscale model, that provides both longer term and short-term forecasts is presented. Ahmed *et al*. use a population diffusion model to model dynamics in detail and use machine learning models to estimate arrival and departure rates from a crisis region. Bayesian methods have also been proposed for forecasting [8].

In practice, forecasts have an expert-driven component where experienced staff provides inputs on likely scenarios that lead to projections and likely evolution. Organizations such as the European Commission have sought to buttress experts with quantitative tools such as the broad risk assessment tools, e.g., the Global Risk Index [7].

Discussion

The results from the validation period offer some insights on the overall approach. Compared to the baseline of using current flows as an estimate of future flows, the improvement of forecast by the use of exogenous socio-demographic indicators suggests the base intuition—that, to some extent, individual decisions to migrate can be at least partially explained by macromeasures.

One limitation of machine learning approaches like the one employed herein is the notion of causality. Under the current modeling framework, we are unable to infer causality between macroindicators and resulting mixed-migration flows. Alternative model forms, such as causal networks or reasoning methods, may be needed for such reasoning.

A quantitative evaluation in this application is challenging. The mixed-migration flows estimated through various sources may not reflect ground truth information. Several populations on the move, irregular migrants for example, are not well documented. While error metrics such as those presented in Table 1 can be computed based on estimates, "true" error rates of point forecasts may never be known. Furthermore, evaluation of confidence intervals and scenario forecasts are impossible to do quantitatively.

The evaluation of the model for Ethiopia over a seven-year period suggests that the forecasts provide errors within several thousand persons per year. However, in three instances, the model missed the forecast. This occurred for Saudi Arabia and South Africa, where the data suggests volatility in migration volumes.

The evaluation results indicate missed forecasts for highly volatile countries could warrant specific models aimed at change detection in flow or macroindicator patterns. This investigation could yield useful insights on migration onset conditions.

Scenario building backed by quantitative methods has so far had small penetration in the humanitarian sphere. This research is a first step toward implementing the use of modern statistical approaches to aid planning. The causal inferences between indicators and outcomes may need even more attention for this type of work to be even more appreciated by practitioners.

The model also enables us to put a quantitative and relative weight to different drivers of migration, which allows us to better understand why people are moving. Better understanding exactly what drives people to move, and how changes in a range of indicators may affect the decision to move, could also enable more targeted and tested interventions aimed at providing people the capability to make informed choices about whether to stay or to migrate, in turn providing a useful contribution to current policy and programmatic discourse based on solid evidence.

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