Time series forecasting for humanitarian aid

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Abstract

This work presents a method for predicting migratory flows from African and Middle Eastern countries to Italy, Spain, and Greece. The challenge of this prediction is due to the complex factors affecting migration. We created a customized dataset, **VAL2G**, with features related to this task and employed various forecasting models, including ARIMA, KalmanFilter and a transformer-based model called Temporal Fusion Transformer (TFT). Comparing the results obtained with the above methods, TFT over performed the chosen baseline, ARIMA, in the prediction of migratory flows. Code and dataset respectively available to the following links: code, dataset.

I. Introduction

Predicting migratory flows is crucial in managing humanitarian aid and determining the appropriate size of refugee camps. However, this forecast is challenging due to the numerous and complex factors such as politics, climate, social and economic issues. To tackle this issue, data-driven approaches are necessary. Despite advancements in collecting migration data and improving data collection methods, most data sources still lack sufficient frequency, definitions, coverage, accuracy, and quality assurance, particularly in terms of data on migration drivers like conflicts, human rights, and the economy. Effective forecasting requires high-quality data with accurate, timely and frequent information.

A. Project overview

To develop a practical and reliable forecasting tool for predicting the influx of migrants from African and Middle-Eastern countries to Italy, Spain, and Greece, we carried out the following steps:

- **Dataset creation**: we tailored a customized dataset step by step with several features related to our task and we considered the best-correlated features to the number of migrants per month.
- **Models deployment**: with the tailored dataset, we employed various forecasting models, including ARIMA and a transformer-based model.

II. Related Work

A. Time-Series Forecasting

Time-Series Forecasting is a widely studied problem in both Statistics and Machine-Learning. It involves using available information to predict future values of a target series. The literature can be divided into two opposing perspectives: those who are skeptical about the effectiveness of Deep Learning for this task and those who strongly support it. In this work, we will examine both approaches and compare a Deep Learning approach to a statistical method as a benchmark.

B. ARIMA

ARIMA, as described in [1], is a widely recognized statistical model known for its high effectiveness in forecasting tasks. We chose this model as a baseline due to its well-established reputation. The name ARIMA is derived from three components: AR (Auto-Regression), MA (Moving Average), and I (Integrated, referring to the Differentiation process).

*1) **AR**:* ARIMA is an auto-regressive model. Specifically, the predictions are computed according to the following (1):

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_n z_{t-n} + \alpha_t \tag{1}$$

where:

- The prediction is computed using only the previous terms of the series
- ϕ_s coefficients are computed just like a linear regression
- A White Noise Term is added (α_t)
- An hyper-parameter p is used to set the number of previous values to consider

*2) **MA**:* Secondly, the Moving Average is computed according to (2)

$$MA_t = \frac{1}{n} \sum_{i=-m_1}^{m_2} \theta_i z_{t-i} \tag{2}$$

Where m_1 is the number of periods before t, m_2 is the number of periods after t, $n = m_1 + m_2 + 1$ is the total number of sum elements and θ_i is the weight of i-th term.

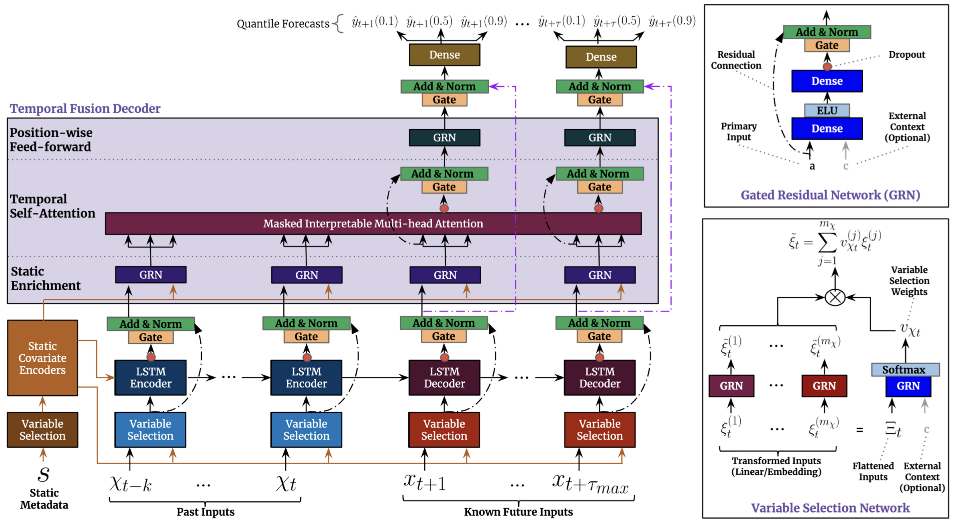

Fig. 1: General architecture of Temporal Fusion Transformer. Notice GRN and VSN

*3) **I**:* Now we have to consider the so-called *Differentation process*. Specifically, each term is substituted with the difference between itself and previous value of the series according to (3)

$$z'_t = z_t - z_{t-1} \tag{3}$$

Notice that this process can be performed more than once.

C. Kalman Forecaster

The Kalman filter [2] is an algorithm used to estimate the state of a dynamic system based on incomplete and uncertain measurements. It is based on the assumption that the system state is describable by a Gaussian probability distribution. The Kalman filter uses a series of iterative steps to estimate the state of the system:

- **State prediction**: based on the available information about the state of the system and the dynamics of the system, the state of the system is estimated for the next time interval.
- **Estimate correction**: new measurements are used to correct the estimate of the state of the system and obtain a more accurate estimate.
- **Probability distribution update**: new information is used to update the probability distribution of the state of the system.

In general, the Kalman filter uses a combination of information about the dynamics of the system and measurement data to estimate the state of the system efficiently and accurately.

Regarding forecasting with a Kalman filter, the prediction from the state prediction step is used for future forecasting of the system state. In our case, Darts' built-in version of Kalman Filter has been adopted.

D. Temporal Fusion Transformer

Temporal Fusion Transformer [3], from now on TFT, is a recent model based on Encoder-Decoder Architecture with a multi-head interpretable attention mechanism. In Fig. 1, an overview of the model's entire architecture is provided. The noticeable parts of the model are:

*1) **GRN**:* Gated Residual Network is a block of TFT where the input *a* and an *optional context vector* pass through Dense Layers and Exponential Linear Unit layer. The main purpose of this block is to avoid the model using non-linearity when it's not needed.

*2) **Variable Selection Network**:* Variable Selection Network is the feature selection network of TFT. A sort of importance score is computed and then features are selected according to it. This allows the model to be interpretable and to become faster.

E. Original Datasets

In order to complete the dataset that we used to perform our experiments, several features from different datasets have been joined. More specifically, we took the following datasets to construct ours:

- **Climate Change Knowledge Portal** [4]: from this source features related to climate have been extracted.
- **United Nations Inflow Records** [5]: from this source, we extracted data related to the number of people coming to Europe. In other words, this is our target time series.
- **NASA's EARTH DATA** [6]: Earth's Data by NASA provided us with information about rain and climate in general.
- **UNDP** [7]: data concerning human development composite indices.
- **ACLED** [8]: Collections of data concerning humanitarian crises with the number of victims and other information. The data were taken from newspaper articles, tweets, and the like.
- **BDI** [9]: Collections of data concerning currency exchange rates.

III. METHODS

A. Dataset Creation

The combination of all these data made it possible to build a never-seen-before dataset that was used to test the models. We decided to call it **VAL2G Dataset**. In particular, it's important to notice that all of these datasets were constructed taking into consideration that the countries of arrival can only be Italy, Spain and Greece, while those of destination are identified in 23 regions of *Africa* and *Middle-East* (those with the most prominence within the datasets). With VAL2G, the distribution of inflow by country of origin to one of the 3 destination countries divided along the time axis is presented in Fig. 2. And again, the number of deaths from armed clashes in the year 2022 is shown in Fig. 3.

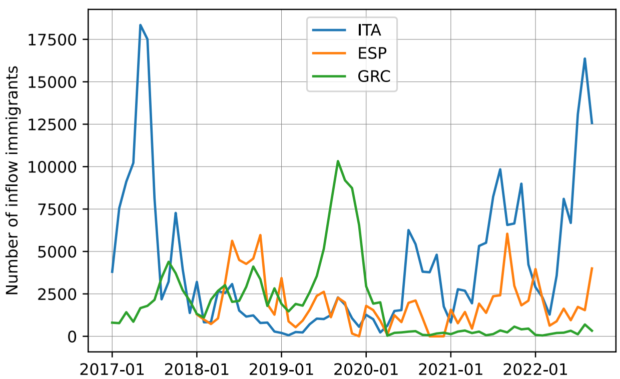

Fig. 2: Total inflows to Italy,Spain and Greece

All the data are monthly based: this is the finest granularity that we found online and in addition, for the context in which this project is placed, it would make no sense to guarantee a daily prediction as it would not be usable. The final dataset is composed of the following features:

- **Monthly inflow** [5]: migrant from a departure country to the arrival country.
- **Fatalities** [8]: number of death in the country of departure.
- **HDI** [7]: human development index, i.e. statistic composite index of life expectancy, education, and per capita income indicators.
- **Distance Departure Destination** [10]: distance between capitals of departure and destination country in Km.
- **Percentage of currency change** [9]: currency change rate with respect to the previous month.
- **Sum Inflow** [5]: total migrants' inflow per country of arrival.
- **Date**: month and year.
- **Destination country** [5]: destination country's *ISO* code.
- **Departure country** [5]: departure country's *ISO* code.

Concerning climate data (minimum, maximum, and average temperatures, precipitation volumes, etc.), we decided to avoid their insertion inside **VAL2G**. In fact, according to Schutte et al. [11], this kind of data has a really poor correlation with migration. In fact, the real core of the article is the claim: "Climatic conditions are weak predictors of asylum migration."

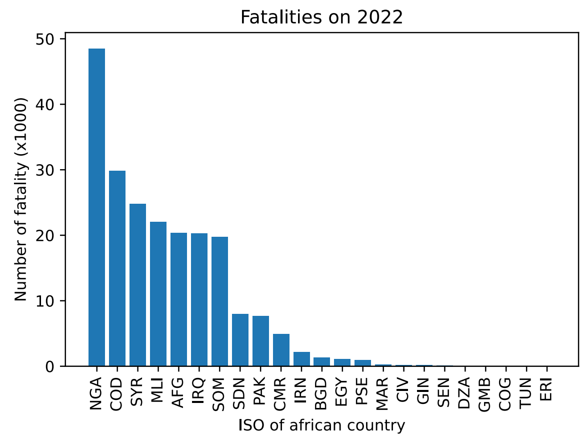

Fig. 3: Number of fatalities on 2022 in each departure countries

IV. EXPERIMENT

A. Experimental setup

In the context of time-series forecasting, the notion of *backtesting* refers to the process of assessing the accuracy of a forecasting method using existing historical data.
To achieve this, the training of the model is carried out over a time span equal to the entire dataset up to the month to be predicted; the target month will be used as test of the model. Subsequently, backtesting continues and uses the time span from the beginning of the available data up to one month before the target month as the training dataset. Backtesting ends when the model is only trained on the first available month in the dataset and validated on the entire remaining dataset.
Following a data-driven approach (from the VAL2G dataset), backtesting is only performed on the **last 10 months** from the end of the dataset, i.e. the most recent 10 months.

B. Metrics

In order to validate our models, we decided to adopt two performance indicators: *Mean Absolute Error* and *Mean Absolute Percentage Error*. Mathematically speaking, they can be defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_{pred} - y_{true}| \tag{4}$$

Fig. 4: Backtest results for Italy obtained by TFT(Left) and ARIMA(right). Notice that TFT model obtains better predictions generally, especially in the last points.

	ITALY		GREECE		SPAIN	
Model	MAPE	MAE	MAPE	MAE	MAPE	MAE
TFT	25.96	1265	75.35	213	40.38	1061
KalmanFilter	25.6	1564	139	229	40	838
ARIMA	30.07	2065	105	393	44.35	525

TABLE I: The table shows the results obtained for different countries by different models.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|100\frac{y_{true} - y_{pred}}{y_{true}}| \tag{5}$$

As it is clearly shown in the formulas, MAPE indicates the percentage error of the predictions and it's important because it states the relative error of our model. On the other side, MAE provides us with the real number of migrants that are wrongly predicted.

C. Results

1) Statistical models: : Since the Statistical models that we choose to adopt do not support covariates, we performed backtest using only the series itself. In Fig. 4, a comparison between the results obtained with TFT and ARIMA is provided. Results obtained for Italy using ARIMA and KalmanForecaster are quite good but worse then the ones obtained using Transformer. Concerning Spain and Greece, the results are quite worse with respect to the one obtained for Italy. In Table I all the results are sum up.

2) Temporal Fusion Transformer: For the evaluation of the Temporal Fusion Transformer, we used the entire dataset as outlined in section III. The trained transformer outputs a forecast for each pair of departure and destination countries, and the final prediction for arrivals at a destination country is the sum of predictions from its corresponding departure countries. The results of the best training for Italy are encouraging, with a MAPE of 25.96 and a MAE of 1265, as depicted in Fig. 4 (left).

However, the performance of the transformer for Spain and Greece, where the quality of data is lower than that of Italy, is not as strong as the Italian results. We observed that for some departure-destination pairs, the model provided good results, as shown in Fig. 7 and Fig. 6. However, for other country pairs, the forecast was less accurate.

Output chunk	Input chunk	Hidden size	Drop out	Optimizer
2 months	24 months	16	0.3	Adam

TABLE II: The table shows the hyperparameters used during the training of TFT model

The results with Temporal Fusion Transformer are obtained with the following hyperparameters set up in Table II.

One advantage of the Temporal Fusion Transformer is its interpretability. As an example, we present an illustration of feature importance obtained from one of the models during the backtest in Fig. 5.

V. Conclusion

In this study, we created a new dataset aimed at forecasting migrant arrivals in Italy, Spain, and Greece. We then applied a deep-learning approach to tackle the problem, using classical statistical models like ARIMA and Kalman Forecaster as a benchmark. We are pleased to report that our deep-learning-based solution outperformed the classical statistical models. Furthermore, the performance of our Temporal Fusion Transformer (TFT) model can be enhanced by incorporating additional data into the dataset to provide the model with new learning features.

A. Future works

Although the results are good, the forecasting method is still perfectible. The main way to do this is to collect more data. Having more time series data the transformer will learn in a more robust and consistent way. It is also possible to add new features. Data such as bilateral pacts between countries of departure and destination would certainly improve the prediction. In addition, transforming our model into an incremental one could be really interesting. In fact, a framework able to update constantly month by month could be something to appreciate by far.

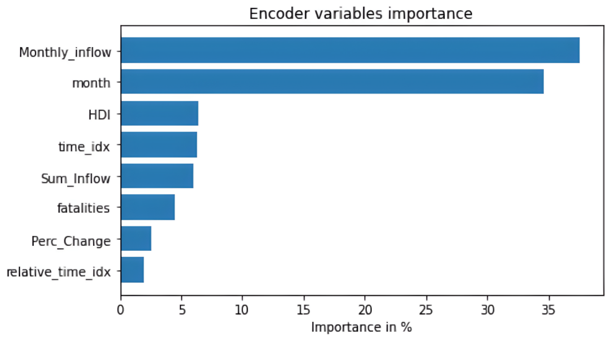

Fig. 5: Features Importance of TFT model

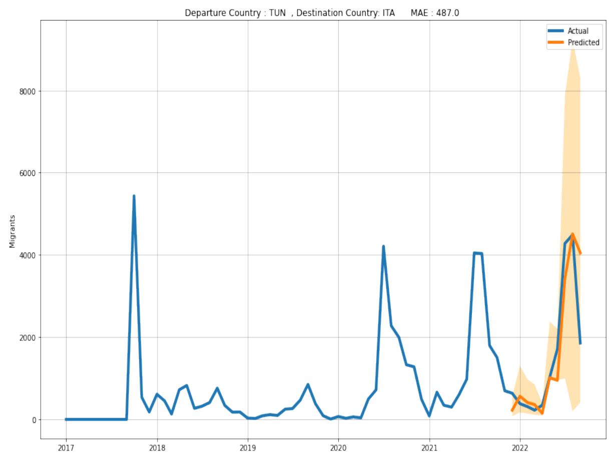

Fig. 6: Forecast for migrants going from Tunisia to Italy

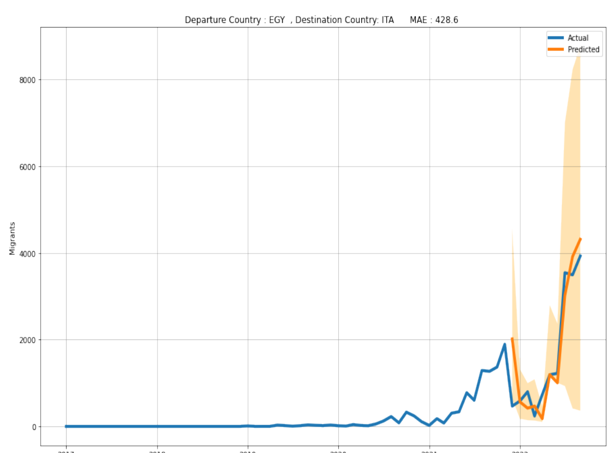

Fig. 7: Forecast for migrants going from Egypt to Italy

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