ABSTRACT

Being able to model and predict international migration as precisely as possible is crucial for policy making. Recently Google Trends data in addition to other economic and demographic data have shown to improve the prediction quality of a gravity linear model for the one-year ahead predictions. In this work, we replace the linear model with a long short-term memory (LSTM) approach and compare it with two existing approaches: the linear gravity model and an artificial neural network (ANN) model. Our LSTM approach combined with Google Trends data outperforms both these models on various metrics in the task of predicting the one-year ahead international migration to 34 OECD countries: the root mean square error has been divided by 5 on the test set and the mean average error by 4. This positive result demonstrates that machine learning techniques constitute a serious alternative over traditional approaches for studying migration mechanisms.

KEYWORDS
forecasting, Google Trends, long short-term memory, migration, prediction, recurrent neural network

1 INTRODUCTION

Mobility has always been part of human history. In 2017, there were about 258 million international migrants worldwide, of which 150.3 million are migrant workers [34]. Modeling and forecasting human mobility is therefore important, to help formulate effective governance strategies but also to deliver insight at scale to humanitarian responders and policymakers. But at the same time, developing reliable forecasting methods able to predict $T_{i,j}$, the number of people moving at the next time step from a region $i$ to a region $j$ among $m$ origin regions and $n$ destination regions is extremely challenging due to lags or even absence in recent migration data, especially for developing countries [4, 6].

One way to mitigate this lag or lack of data is the use of real-time geo-referenced data on the internet like the Global Database of Events, Language, and Tone (GDELT Project) or Google Trends. Both have been successfully used to make forecasting in various fields [1, 7, 15]. Recently, Böhme et al. [6] demonstrated that adding geo-referenced online search data to predict migration flows yields better performance compared to only using common economic and demographic indices, e.g. the gross domestic product (GDP), and the population size. The authors propose to predict bilateral migration flows of next year with a linear model relying on the Google Trends data captured the previous year.

In this work we use the exact same data, but we replace the linear model by a recurrent neural network (LSTM [21]) that is able to consider the whole history to make predictions. We demonstrate that the prediction quality can be drastically improved by capturing better complex migration dynamics [25] and complex interactions between the many features.

The outline of our work is the following. We first introduce the related work in section 2. In order to make this article more self-contained, we explain in section 3 how the Google Trends features are extracted in Böhme et al. [6] and also briefly introduce recurrent neural networks. We then describe our recurrent neural network approach in section 4. Finally, our approach is evaluated and compared with the previous approach in section 5.

2 RELATED WORK

In traditional models, the problem of predicting $T_{i,j}$ or an estimation of it $\hat{T}_{i,j}$ is usually divided into two sub-problems: (a) predict $G_i$ the number of people leaving a region $i$ (aka production function); and (b) predict $p_{i,j}$ the probability of a movement from $i$ to $j$. Thus we get that $\hat{T}_{i,j} = G_i p_{i,j}$. With ML models, the problem is quite different as the goal is to directly predict $\hat{T}_{i,j} = f(\text{features})$ from a set of features$^1$. There are basically two conventional models: (a) the gravity model; and (b) the radiation model. Gravity models, inspired by Newton’s law, evaluate the probability of a movement between two regions to be proportional to the population size of the two regions $i$ and $j$, and inversely proportional to the distance between them $[2, 23, 28]$. In radiation models, inspired by diffusion dynamics, a movement is emitted from a region $i$ and has a certain probability

$^1$Notice that you could approach the problem the same way as with traditional models but it is not a common practice.
of being absorbed by a neighboring region \( j \). The subtlety here
is that this probability is dependent on the population of origin,
the population of the destination, and on the population inside a
circle centered in \( i \) with a radius equal to the distance from \( i \) to \( j \)'
[31]. Gravity is usually better to capture short distance mobility
behavior, while radiation is usually better to capture long-distance
mobility behaviors [25].

To the best of our knowledge, [29] is the first attempt to use ML
in order to predict human migration. The authors use two ML tech-
niques: (a) "extreme" gradient boosting regression (XGBoost) model;
and (b) deep learning based artificial neural network (ANN) model.
Similarly to us, this approach also attempts to directly predict \( T_{i,j} \)
from the set of features without requiring any production function.
But this approach also exhibits two important differences with our
approach: 1) It uses traditional features for their prediction model,
which is composed of geographical and econometric properties
such as the inter-country distance, median household income, etc.
2) They don’t capture the dynamic aspect since the prediction only
relies on the previous time-step set of features.

More recently, Böhme et al. [6], proposed to use the Google
Trends Index (GTI) of a set of keywords related to migration (ex-
amples: visa, migrant, work, etc.) as a new feature set to make
migration prediction. Böhme et al. [6] rely on a bilateral gravity
model to predict the total number of migrant leaving a country of
origin towards any of the OECD’s destination countries during
a specific year. The gravity models are estimated by a linear regres-
sion. Our approach uses the exact same input data and thus also
relies on the Google Trends Index (GTI) data. But instead of a linear
least squares estimation model, we use a recurrent neural network
(LSTM) that is fed with the complete set of historical features rather
than only the ones coming from the previous time step.

## 3 BACKGROUND

We start by describing the data used for learning and predicting
the migration, giving more details about the Google Trends new
set of features from [6]. We describe the performance metric used
to compare the prediction models also used in [29]. We then briefly
introduce recurrent neural networks.

### 3.1 Data and features sets

Table 1 gives an overview of the features used from the data pro-
vided by Böhme et al. [6]. More specifically, we use following fea-
tures: Gross Domestic Product (GDP) for origin and destination
countries, population size for origin and destination countries [35],
the bilateral Google Trends Index (GTI), migration numbers from
the previous year (IOM 2018), as well as 3 one-hot vectors for en-
coding the origin, destination and the year.

---

**Table 1: The input features used for the different models. Each feature spans from 2004 to 2014 for a pair of origin-destination
country. Refer to subsection 3.1 for a detailed explanation of the Google Trends Index (GTI).**

| Input features \( f_{i,j,t} \) | Description |
|-------------------------------|-------------|
| GDP\(_i,t\)                   | Gross Domestic Product for origin country \( i \) during the year \( t \) |
| GDP\(_j,t\)                   | Gross Domestic Product for destination country \( j \) during the year \( t \) |
| pop\(_i,t\)                   | Population size for origin country \( i \) during year \( t \) |
| pop\(_j,t\)                   | Population size for destination country \( j \) during year \( t \) |
| \( f_{\text{fixed}_i} \)      | Origin country \( i \) fixed effects, encoded as a one-hot vector |
| \( f_{\text{fixed}_j} \)      | Destination country \( j \) fixed effects, encoded as a one-hot vector |
| \( f_{\text{fixed}_t} \)      | Year \( t \) fixed effects, encoded as a one-hot vector |
| GTI\(_{\text{bilateral},i,j,t}\) | Bilateral GTI for a pair origin country \( i \) and destination country \( j \) during a year \( t \) |
| GTI\(_{\text{unilateral},i,t} \times \text{GTI}_{\text{destination},j,t}\) | Current year migration flow from country \( i \) to country \( j \) |

---

2The data can be downloaded from their website, or through an unofficial API [12].
3https://semantic-link.com/
4Google Trends data only starts from 2004 and the migration data stops after 2015.
5This is specific to requests spanning from 2004 to the present.
The performance of prediction models can be evaluated with several metrics also used in [29] and summarized in Table 2. Another approach would have been to use different networks to unfold RNN. As described in figure 1 we use one RNN in charge of predicting the bilateral flows \( T_{i,j} \) and also all the observed migration flows spanning from 2005 to 2013 as output \( T_{i,j} \) since we predict next year migration; (b) a validation set, containing input features on the year 2013 (input features \( i,j \)) and also all the observed migration flows between 2005 and 2013 as output \( T_{i,j} \) since we predict next year migration; (c) a test set, on the year 2014 (input features \( i,j \)) since we

![Image](image.png)

Figure 1: An unfolded gated-RNN with LSTM cells. The left-side corresponds to the folded RNN, while the right-side to the unfolded RNN.

and bilateral aspects. Three different forms of GTI values are then defined:

- The vector of unilateral GTI or \( GTI_{uni} \) contains the GTI values of the set of keywords for the country of origin \( i \) during the year \( t \).
- The vector of bilateral GTI or \( GTI_{bi} \) contains GTI values also specific to the country of destination \( j \). The values are still captured in the country of origin \( i \) during the year \( t \) but the related keywords correspond to the combination of the terms with the name of the destination country (examples: visa Spain, migrant Spain, work Spain, etc.).
- The destination GTI \( GTI_{dest} \), contains only the GTI value of the keyword corresponding to the destination country's name \( j \) (example: Spain) for the country \( i \) and the year \( t \).

**Migration Data.** The data-base OECD [27] provides a yearly incoming migratory flow from 101 countries of origin to the 35 countries member of the OECD from the early 1980's until 2015. Demographic and economic data about each destination and origin countries have been gathered from the World Development Indicators [35].

3.2 Evaluating prediction models

The performance of prediction models can be evaluated with several metrics also used in [29] and summarized in Table 2.

**Common Part of Commuters (CPC):** Its value is 0 when the ground matrix \( T \) and the prediction matrix \( \hat{T} \) have no entries in common, and 1 when they are identical.

**Mean Absolute Error (MAE):** Its value is 0 when the values of both matrices are identical, and arbitrarily positive the worse the prediction gets.

**Root Mean Square Error (RMSE):** Its value is 0 when the values of both matrices are identical, and arbitrarily positive the worse the prediction gets. The main difference with the MAE is that the RMSE penalizes more strongly the large errors.

**Coefficient of determination \( r^2 \):** Its value is 1 when the predictions perfectly fits the ground truth values, 0 when the predictions are identical to the expectation of the ground truth values, and arbitrarily negative the worse the fit gets.

**Mean Absolute Error In (MAE)\( \) on total incoming migrant by destination countries \( u_j = \sum_{i=1}^{n} T_{i,j} \).**

3.3 Recurrent Neural Networks and Long Short-Term Memory (LSTM)

Recurrent neural networks (RNN) [16, 18] and LSTM are types of artificial neural networks (ANN) architectures particularly well suited to predict time-series or sequential data. It allows sharing features learned across different parts of the sequential data to persist through the network and it is also not required to have a fixed set of input vectors. Long short-term memory (LSTM) [5, 9, 18, 20] are special architectures of RNN improving their ability to learn properly long-term dependencies by limiting the risk of vanishing and exploding gradient problems.

Since its first publication, LSTM has recently gained momentum for several applications, including in forecasting, and has been shown to yield better performances in the prediction of time series compared to other ML techniques [13, 14, 19, 22, 24, 30, 33, 36].

4 OUR LSTM APPROACH

As described in figure 1 we use one RNN in charge of predicting the bilateral flows \( T_{i,j} \) with the origin and destination countries one hot encoded for all pairs \( (i,j) \). The RNN has a unique LSTM layer. Another approach would have been to use different networks to estimate the flow for each pair of countries. The amount of data to train each would have been very limited, though.

4.1 Learning models and hyper-parameter optimization

To train the ML models we proceed using three sets [16]: (a) a train set, gathering the input features from 2004 to 2012 (input features \( i,j \)) and also all the observed migration flows spanning from 2005 to 2013 as output \( T_{i,j} \) since we predict next year migration; (b) a validation set, containing input features on the year 2013 (input_features \( i,j \)) and migration flows of 2014 (\( T_{i,j} \)) and migration flows of 2014 (input_features \( i,j \)). A simplified version of our LSTM training is presented in Algorithm 1, while our LSTM evaluation is presented in Algorithm 2. Notice that the span of years presented in the algorithms corresponds to the one used once the validation is completed, i.e., we fit our model on both the training and validation set.
Table 2: The different metrics – \( T \) is the ground truth value, \( \hat{T} \) is the prediction matrix, \( m \) is the number of origin countries, \( n \) is the number of destination countries, \( v_j = \sum_{i=1}^{m} T_{i,j} \) is the number of incoming migrants for a zone \( j \), \( \hat{v}_j \) its prediction.

| Metrics                          | Equations |
|----------------------------------|-----------|
| Common Part of Commuters         | \( CPC(T, \hat{T}) = \frac{2 \sum_{i,j}^{m,n} \min(T_{i,j}, \hat{T}_{i,j})}{\sum_{i,j}^{m,n} T_{i,j} + \sum_{i,j}^{m,n} \hat{T}_{i,j}} \) (1) |
| Mean Absolute Error              | \( MAE(T, \hat{T}) = \frac{1}{m \cdot n} \sum_{i,j}^{m,n} |T_{i,j} - \hat{T}_{i,j}| \) (2) |
| Root Mean Square Error           | \( RMSE(T, \hat{T}) = \sqrt{\frac{1}{m \cdot n} \sum_{i,j}^{m,n} (T_{i,j} - \hat{T}_{i,j})^2} \) (3) |
| Coefficient of determination     | \( r^2(T, \hat{T}) = 1 - \frac{\sum_{i,j}^{m,n} (T_{i,j} - \hat{T}_{i,j})^2}{\sum_{i,j}^{m,n} (T_{i,j} - \bar{T})^2} \) (4) |
| Mean Absolute Error In           | \( MAE_{in}(v, \hat{v}) = \frac{1}{n} \sum_{j}^{n} |v_j - \hat{v}_j| \) (5) |

Algorithm 1: Our training algorithm

```
Data: model : LSTM untrained model
Result: Model is trained
for each epoch do
    for each pair \( i,j \) of origin-destination countries do
        /* gradient descent for each batch: */
        model.fit(input_features_{i,j,04..13}, \( T_{i,j,05..14} \))
    evaluation(model) /* see algorithm 2 */
```

Algorithm 2: Our evaluation algorithm

```
Data: model : LSTM trained model
Result: Model is evaluated
for each pair \( i,j \) of origin-destination countries do
    \( \hat{T}_{i,j,15} \leftarrow \text{model.predict(input_features}_{i,j,04..13} \) \)
    error \leftarrow \text{compute_metrics}(T_{i,15}, \hat{T}_{i,15})
```

Due to the specificity of LSTM, we fit our LSTM time series by time series\(^6\). Therefore we use a batch of size corresponding to the number of years present in the serie. This implies that the gradient descent is applied and the LSTM’s parameters are updated after each propagation of a time series through the LSTM cells (as presented in figure 1). Furthermore the features have been normalized by time series of origin destination using a min max scaler [16]. Our LSTM model uses a bias of 1 for the LSTM forget gate since it has been shown to improve performances drastically [13, 22].

We make use of dropout regularization to reduce the overfitting for both models and ensure a better generalization [3, 11, 32]

\(^6\)By time series we mean sequence of annual migration flows between a pair of origin destination.

For the experiments, we have used three different loss functions: Mean Absolute Error (MAE), Mean Square Error (MSE), and Common Part of Commuters (CPC), as described in [29], equivalent to 1 – cpc with cpc given by equation (1) and adapt them to handle time series.

We optimize the following hyperparameters and present them along with their optimal value: loss function - MAE using adam optimizer, number and size of hidden layers - 1 layer of width 50, number of epochs - 50, and dropout - 0.15.

5 RESULTS AND DISCUSSION

We carry out experiments comparing the performance of our LSTM approach with two other models:

(a) The bilateral gravity model estimated through an OLS model as presented in [6] whose gravity equation is represented below:

\[
\log(T_{i,j,t+1}) = \beta_1 GTi_{i,j,t} + \beta_2 GTi_{i,j,t} \times GTd_{i,j,t} + \beta_3 \log GDP_{i,t} + \beta_4 \log GDP_{j,t} + \beta_5 \log GDP_{i,j,t} + \beta_6 \log GDP_{i,j,t} + f_{\text{fixed}_i} + f_{\text{fixed}_j} + f_{\text{fixed}_{i,j}} + \epsilon_{i,j,t}
\]

(b) A deep learning based artificial neural network model (ANN model) as proposed in [29]. Our ANN is composed of densely connected with rectified linear units (ReLU) activation layers. We use the same model for all the predictions with a time step of 1 year. This means that the ANN receives as input the set of features \( \text{input f eatures}_{i,j,t} \) described in Table 1 and outputs the predicted next-year migration flow \( T_{i,j,t+1} \). We optimize the following hyperparameters and present them along with their optimal value: loss function - MAE using adam optimizer, number and width of hidden layers - 2 layers of width 200, training batch size - 32, number of epochs - 170 and dropout - 0.1.
Table 3: Comparison of the 3 models for the specified metrics. The values shown are by pair (train - test). Bold values indicate the best values per column. There are on average 742 migrants and 46 119 incoming migrants.

| Models       | CPC   | MAE   | RMSE  | \( r^2 \) | MAE_in |
|--------------|-------|-------|-------|-----------|--------|
|              | train | test  | train | test      | train  |
| Linear Regression | 0.871 | 0.866 | 819   | 877       | 6 100  |
| ANN          | 0.931 | 0.834 | 119   | 306       | 818    |
| LSTM         | 0.945 | 0.892 | 96    | 225       | 639    |

Our source code is available on the following git repository: https://github.com/aia-uclouvain/gti-mig-paper. It contains the script to extract the Google Trends Index, the Google Colab notebook to build the different models, as well as the data we used. The code is written in python and uses the Keras library, which runs on top of TensorFlow.

In order to assess the predictive power of each model, we use a test set represented by every migration flow taking place in 2015 which represent a bit less than 10% of the whole data.

The table 3 shows the results of each model on both the training and test sets for the five metrics we mentioned in the Related Work section.

We can observe that our ML models perform much better than the Böhme et al. [6]'s linear model. Indeed, with the same data, the ANN beats the first model in almost every metric while the LSTM model completely outperforms it in all the measures. The ANN model fits very well the training data but it does not seem to generalize as well as the LSTM model as shown by their performance on the test set. We can draw from these first results that the LSTM is the best predictive model among these three.

Since the RMSE values are always way higher than the MAE (between 5 and 7 times larger) we can conclude that the models tend to make a few really large errors. This can be explained by analyzing the data. In the dataset, the mean value of migration flows between 2 countries during a year is 742 but the median value is only 17 while the maximum is about 190 000. This indicates that our dataset is very sparse: there is a lot of near zero observations (40% are below 10) for a very few extremely important ones (less than 2% reach 10 000). One can notice that the mean absolute errors of the different models are very important compared to the mean annual migration flows (742 and 46 119, see table 3 caption) but these values are heavily biased by the sparsity of the data and by the large errors made on the really large migration flows, e.g. the USA and Spain. In the case of Spain notice that there has been an important drop in incoming migration flows in 2008 due to the 2007–2008 financial crisis [8].

In order to have a better visualization of the predictive power of the models, we represent in figure 2 the scatter plot of the 3 models for the test set only. The graph reflects well the sparse nature of the data as shown by the density of points along the x-axis. As expected following the first results, we can observe that the linear model does not provide very accurate predictions. The ANN model, on the other hand, shows a stronger tendency to underestimate the ground truth values. Ultimately, the LSTM's estimations are the ones sticking the most to the actual migration flows which confirms our first assumption.

Finally, figure 3 shows the error of the total number of incoming migrants per destination country per year for each model. We can observe that whatever the model, for the majority of countries and years, the estimation error is close to null and that the big errors often appear in the same countries of destination. Knowing that, we can see that the heatmaps of the ANN model and of the linear regression in figure 3 highlight their tendency to underestimate the migration flows especially for the last year (the test year).

To compare these errors with the actual migration flows, we represent in the rightmost heatmap in figure 3 the ground truth values of the total number of incoming migrants per destination country and per year in descending order. With this figure we can clearly see that the errors we make are mostly for the countries with important incoming migration flow.
we would like to apply the latest interpretability techniques (see ARC convention on “New approaches to understanding and The authors acknowledge financial support from the UCLouvain (LSTM) artificial recurrent neural network (RNN) architecture. Our modelling global migration trends” (convention 18/23-091).

REFERENCES

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6 CONCLUSION

Böhme et al. [6] have recently demonstrated that including Google trends data in the set of standard features could improve the migration prediction models. In this work, relying exactly on the same data, we improved the quality of the prediction significantly by replacing the linear model used in by a Long short-term memory (LSTM) artificial recurrent neural network (RNN) architecture. Our experiments also demonstrated that the LSTM was outperforming a standard ANN on this task.

One drawback of our machine learning approach is that we lose interpretability of the model and predictions despite the high interpretability potential of Google search keywords. As future work, we would like to apply the latest interpretability techniques (see [26]) to better identify what the most important features for making high quality migration predictions. This would equip economists and experts in migration with new tools to shed light on migration mechanisms.

Figure 3: Heatmaps of the error on total incoming migrants for 34 OECD countries on the test year (2015) showing how well each model fits the data. From left to right: Linear Regression Model, ANN Model, and LSTM Model. The rightmost figure is the ground values for the total number of incoming migrants by destination countries. Countries are in descending order of total incoming migrants.

6 CONCLUSION

Böhme et al. [6] have recently demonstrated that including Google trends data in the set of standard features could improve the migration prediction models. In this work, relying exactly on the same data, we improved the quality of the prediction significantly by replacing the linear model used in by a Long short-term memory (LSTM) artificial recurrent neural network (RNN) architecture. Our experiments also demonstrated that the LSTM was outperforming a standard ANN on this task.

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| English | French | Spanish |
|--------|--------|---------|
| applicant | candidat | solicitante |
| arrival | arrivee | llegada |
| asylum | asile | asilo |
| benefit | allocation sociale | beneficio |
| border control | controle frontier | control frontera |
| business | entreprise | negocio |
| citizenship | citoyennete | ciudadania |
| compensation | compensation | compensacion |
| consule | consulat | consulado |
| contract | contrat | contrato |
| customs | douane | aduna |
| deportation | expulsion | deportacion |
| diaspora | diaspora | diaspora |

### Table 4: List of main keywords – First part [6, Table 1]

A USED KEYWORDS

Tables 4 and 5 contain the set of main keywords: "For GTI data retrieval, both singular and plural as well as male and female forms of these keywords are used where applicable. In the English language, both British and American English spelling is used. All French and Spanish keywords were included with and without accents" [6, Table 1].
Table 5: List of main keywords – Second part [6, Table 1].

| English    | French       | Spanish   |
|------------|--------------|-----------|
| discriminate | discriminer | discriminar |
| earning    | revenu       | ganancia  |
| economy    | economie     | economia  |
| embassy    | ambassade    | embajada  |
| emigrant   | emigre       | emigrante |
| emigrate   | emigrer      | emigrar   |
| emigration | emigration   | emigracion|
| employer   | employer     | empleador |
| employment | emploi       | empleo    |
| foreigner  | etranger     | extranjero|
| GDP        | PIB          | PIB       |
| hiring     | embauche     | contratacion |
| illegal    | illegal      | illegal   |
| immigrant  | immigre      | inmigrante|
| immigrate  | immigrer     | inmigrar  |
| immigration | immigration | inmigracion |
| income     | revenu       | ingreso   |
| inflation  | inflation    | inflacion |
| internship | stage        | pasantia  |
| job        | emploi       | trabajo   |
| labor      | travail      | mano de obra |
| layoff     | licenciement | despedido |
| legalization | regularisation | legalizacion |
| migrant    | migrant      | migrante  |
| migrate    | migrer       | migrar    |
| migration  | migration    | migracion |
| minimum    | minimum      | minimo    |
| nationality | nationalite | nacionalidad |
| naturalization | naturalisation | naturalizacion |
| passport   | passeport    | pasaporte |
| payroll    | paie         | nomina    |
| pension    | retraite     | pension   |
| quota      | quota        | cuota     |
| recession  | recession    | recession |
| recruitment | recrutement  | reclutamiento |
| refugee    | refugie      | refugiado |
| remuneration | remuneration | remuneracion |
| required documents | documents requis | documentos requisito |
| salary     | salaire      | sueldo    |
| Schengen   | Schengen     | Schengen  |
| smuggler   | trafiquant   | traficante |
| smuggling  | trafic       | contrabando |
| tax        | tax          | impuesto  |
| tourist    | touriste     | turista   |
| unauthorized | non autorisee | no autorizado |
| undocumented | sans papiers  | indocumentado |
| unemployment | chomage     | desempleo  |
| union      | syndicat     | sindicato |
| unskilled  | non qualifies | no capacitado |
| vacancy    | poste vacante | vacante |
| visa       | visa         | visa      |
| waiver     | exemption    | exencion  |
| wage       | salaire      | salario   |
| welfare    | aide sociale | asistencia social |