Quantifying the improvement in human living standard, as well as the city growth in developing countries, is a challenging problem due to the lack of reliable economic data. Therefore, there is a fundamental need for alternate, largely unsupervised, computational methods that can estimate the economic conditions in the developing regions. To this end, we propose a new network science- and representation learning-based approach that can quantify economic indicators and visualize the growth of various regions. More precisely, we first create a dynamic network drawn out of high-resolution nightlight satellite images. We then demonstrate that using representation learning to mine the resulting network, our proposed approach can accurately predict spatial gross economic expenditures over large regions. Our method, which requires only nightlight images and limited survey data, can capture city-growth, as well as how people’s living standard is changing; this can ultimately facilitate the decision makers’ understanding of growth without heavily relying on expensive and time-consuming surveys.

1 Introduction

The ongoing big data and machine learning revolution has greatly contributed to quantifying economic development. However, although massive data is available for developed countries, the developing countries still suffer from the lack of reliable economic data. This polarization also exists in the quality of data since the recorded data in developing countries has been known to be unstructured and inaccurate [1], thereby making the useful data even more scarce. All these challenges have greatly hindered the accurate modeling of economic conditions in the developing world.

Knowing how people live and the rate of improvement of their living standard are fundamental components of many decision making processes such as urban development, policy effectiveness evaluation, and conservation planning, etc. However, the lack of sufficient high-quality data in developing countries can result in poor decisions which can in turn lead to bad development policies. On the other hand, apart from this low-quality economic data obtained from time- and labor-intensive surveys, the massive amount of high-resolution nightlight satellite images forms a more reliable source of data for developing countries. Therefore, new machine learning-based methods that can more effectively exploit the power of nightlight satellite images to predict economic indicators and explicitly quantify the economic growth of different regions.

In this paper, we propose a new network science- and representation learning-based approach to explicitly capture the complex relationship between the economic growth of various regions, and also predict economic indicators over large regions. To this end, we propose a novel gravity-based model to create, for the very first time, a dynamic economic-growth network by using massive amount of nightlight satellite images and limited survey data.
nightlight satellite data. We also demonstrate that mining this network with representation learning techniques like node2vec [2] can help us accurately predict economic indicators over large regions.

Overall, we demonstrate that by using our proposed gravity model and publicly available satellite data, we can create large-scale economic-growth networks in a largely unsupervised manner (with the exception of fine-tuning a few hyper-parameters). Mining this network can give us features relevant to economic growth which can be further used for accurately predicting economic indicators. This way, we can clearly obtain socio-economic features for large regions without relying on expensive and time consuming surveys. Hence, our method can be used for large-scale economic modeling in the developing world.

2 Previous Work

A prior deep learning approach on nightlight satellite images for poverty prediction was proposed in [3]. Since using a deep learning model directly with nightlight images requires a large dataset with millions of samples with labelled economic data, Jean et al. address this problem by applying a transfer learning technique with an ImageNet-pretrained deep network. As a result, feature embeddings from the CNN model can explain 75% of variation in local-level economic outcomes [3, 4]. Other prior works extend such ideas to population estimation [5] and crop yield prediction [6]. Although this prior art predicts poverty via satellite images, this prediction is mostly spatial in nature. Consequently, the temporal aspects of economic growth have been largely ignored in prior works. Moreover, most CNN models have an inherent problem of being non-interpretable. This is especially critical for applications where decisions must be made based on the machine learning model output (for instance, for urban planning, etc.). Specifically, using interpretable machine learning models can help to actually understand the underlying factors behind the model output in order to more accurately target such factors while making decisions.

In our work, we address both limitations above. Specifically, since we build economic-growth networks from the satellite data, we can analyze their properties like community structure [7] to understand which locations experience growth over time; this will result in a much more interpretable model than, say, the output of a CNN. Also, while previous work lacks temporal analysis and does not predict the future development trends, our dynamic network can be potentially used for spatio-temporal predictions (and not just spatial!). We show some preliminary results for accurate spatiotemporal predictions using our proposed approach.

3 Proposed Approach

Our approach can be divided into three parts: network construction, network mining and regression.

3.1 Economic Gravity-Based Network Construction Model

Our gravitational model aims to predict the economic indicators. To achieve this, we divide the region of interest into smaller grids and treat each grid as a node in the network. For example, we consider economic prediction for Tanzania, and thus we divided the entire country into 50 × 51 grids where each grid has an area of approximate 524.4km² (22.9km ×22.9km). For each node (grid), we draw undirected edges to all the other nodes with a weight calculated with the following gravitational equation:

$$W_{i,j} = \frac{M_i \cdot M_j}{R^P}$$

where, $W_{i,j}$ is the weight on the edge from node $i$ to $j$, $M_i = \log(I_i + 1)$ is the total grid nightlight log-intensity for node $i$, and $R$ is the normalized distance between each node (ranging from 0 to 1). Parameter $P$ controls the trade-off between forming links based on intensity vs distance.

After drawing edges for all nodes, the network is fully connected with total $2550 \times 2550$ edges. Since there are many edges with low gravity weight, we set a threshold $\tau$ to remove low gravity links. Finally, to prevent nodes from getting disconnected from the network, we rewire the nodes with less than $K$ links to their $K$ nearest neighbors; this is similar to the $K-\tau$ method introduced in [8].

3.2 Network Mining

Intuitively, based on the gravity network, we can see that if a node (i.e., the location) is more developed, it will have a higher nightlight intensity and, hence, more links to nearby node; that is, if a
community [7] of economically wealthy locations in the network grows over time, it is highly likely that this region is experiencing rapid economic growth (see Fig. 1). These community-based features can be captured by existing representation learning frameworks like node2vec [2]. The algorithm is a biased random walk on a graph, and the probability to travel between two nodes is a function of edge-weight between them. Two adjustable parameters, \( p \) and \( q \) are introduced representing priority of the walk to trade-off between exploration and exploitation. Here we choose the \( q = 0.5, p = 1 \) in node2vec implementation, smaller value of \( q \) is emphasized to prefer exploitation over exploration.

As illustrated in Fig. 1c and d, if the number of nodes in the community grows, node2vec will generate similar features for the nodes that belong to a similar community. Moreover, since the network communities share similar characteristics, these locations will most likely share similar consumption index. Hence, the latent developing trend, as well as the similarity between nodes can be captured via network representation learning, thereby resulting in features that are easier to interpret. Also, visualizing the dynamic network can also inform decision makers of other latent trends (e.g., location X became similar to location Y in terms of economic development).

### 3.3 Regression Model over Economic Gravity-Based Features

We next convert the walks simulated from node2vec neighborhood search strategy into walks of light intensities by replacing the grid ID with its grid intensity. Then, the expected value of intensity at each step \( i \in (1, L) \), \( L = \text{Walk length originating from node } k \in (1, K) \), \( K = \text{Number of grids} \) is calculated. Therefore, the feature vector of a node represents the expected value of intensity at each step of a random walk originating from that node.

Finally, the features generated above for each node, and the corresponding economic indicators are used in a regression model (e.g., Random Forest or K-Nearest Neighbor regression or Bayesian) for training and testing. Note that, our proposed method does not require labelled economic data to build the economic-gravity network. More precisely, we can derive these community-based features for a large number of locations and use them for economic prediction on locations that do not have large-scale surveys. Therefore, our model can be used as an alternate way to quantify economic condition and growth trends in developing countries without heavily relying on surveys which are, time-, money-, and labor-intensive.

### 4 Results

#### 4.1 Experimental Setup

We use monthly nightlight images from National Oceanic and Atmospheric Administration (NOAA) with a 15 arc-second spatial-resolution geographic grid [9]. For economic prediction, we use Livining Standards Measurement Study (LSMS) survey data with consumption expenditure and coordinates (measured in Longitude and Latitude) from Tanzania, National Panel Survey (NPS) for the year 2012 – 2013, 2014 – 2015, and Malawi, Integrated Household Panel Survey (IHPS) for the year 2013, 2016 [10] as our ground truth for training and prediction. We conduct spatial and spatio-temporal predictions in the current version of this paper. For the gravity model, we set \( \tau = 5 \) and
4.2 Economic Prediction Results

In this section, we present results for spatially predicting economic indicators at several locations in Tanzania and Malawi. After, preprocessing the LSMS survey data-set (cleaning, binning, and mapping) we can recover around 500-1000 data points per set per year. We split it 50% for training and 50% for testing. Next, we build economic-gravity network from average nightlight images available for the corresponding year. After computing the features for all the nodes in the network (which are grids on the map), we associate the each node to the nearby houses with a Manhattan distance threshold of $0.25$ degree of longitude and latitude which is equivalently an $11$ km region around the grid center. We conducted experiments with 100 different training-testing splits to obtain statistically significant results.

We evaluate our model via calculating $R^2$, which represents the amount of variance explained by the model. The prediction results (for the median $R^2$ value) are shown in Fig. 2. As evident, Fig. 2(a) shows $R^2$ for the Random Forest model used on the training set, while Fig. 2(b) shows $R^2$ for the testing set for the same model. Similarly, Fig. 2(c) shows $R^2$ for the testing set with the K-Nearest Neighbor model. Clearly, the $R^2$ on the testing set for both regression models is high which indicates that features generated by the node2vec algorithm on the proposed gravitational network capture very relevant economic features. The $R^2$ results for the rest of the experiments are summarized in Table 1.

Figure 2: Coefficient of determination, $R^2$ on test sets for (a) Bayesian-Ridge Regression (BRR), (b) Random-Forest Regression (RFR), (c) K-Nearest-Neighbors Regression (KNNR) (d) Linear Regression (LR) for Tanzania 2013. Similarly, (e), (f), (g) and (h) represent $R^2$ on test sets for BRR, RFR, KNNR, and LR respectively for Malawi 2013. High $R^2$ for testing set shows that node2vec features for economic-gravity networks indeed capture economic information.

Table 1: Spatial Predictions - Test $R^2$ by region and year for models BRR, RFR, KNNR, and LR.

| Country | Year | BRR Test $R^2$ | RFR Test $R^2$ | KNNR Test $R^2$ | LR Test $R^2$ |
|---------|------|---------------|----------------|-----------------|-------------|
| Tanzania | 2013 | 0.61718       | 0.52485        | 0.61048         | 0.67821     |
| Tanzania | 2015 | 0.60326       | 0.41516        | 0.47981         | 0.63308     |
| Malawi  | 2013 | 0.58167       | 0.54436        | 0.51313         | 0.58330     |
| Malawi  | 2016 | 0.44194       | 0.45513        | 0.34388         | 0.43937     |

$K = 3$ for Tanzania, and $\tau = 2$ and $K = 1$ for Malawi as a function of the country size and density of light-intensity.

Of note, our test-set $R^2 = 0.5$ is close to the $R^2$ reported in the prior work for Tanzania [3].
4.3 Growth Monitoring via Community Detection on Economic-Gravity Networks

For monitoring economic growth-similarity trends, we show our results in Fig. 4(a)-(c) for high resolution community detection on economic-gravity networks for 2012, 2013, and 2014 nightlight data. The number of communities in the network varied from 23 in 2012, to 20 in 2013, to 18 in 2014. This is in agreement with our initial hypothesis presented in Fig. 1 that when economic growth becomes similar among different regions, they will get merged into bigger communities. This is clearly evident from Fig. 4(a,b) when the communities merge due to similar growth trends in the Northwestern part of Tanzania (red arrows), while a community breaks down into two in the Southeastern part (violet arrow). Therefore, these dynamic growth trends can be easily captured by our network-based approach. This further provides more information to decision makers about which locations are experiencing similar/different growth rates.

5 Conclusion and future work

We have proposed a new dynamic gravity-based network model for quantifying economic growth across a large region. To this end, we have used representation learning on a gravity-network to extract different growth-related features. Our results have demonstrated that our proposed approach can indeed accurately predict the spatial and spatio-temporal gross economic expenditures. We have further used dynamic community structure to monitor the growth of different regions over time.

For future work, we plan to improve upon our current temporal economic predictions by building representation learning methods for dynamically changing networks.
References

[1] Justin Sandefur and Amanda Glassman. The political economy of bad data: Evidence from african survey and administrative statistics. *The Journal of Development Studies*, 51(2):116–132, 2015.

[2] Aditya Grover and Jure Leskovec. Node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016.

[3] Neal Jean, Marshall Burke, Michael Xie, Matthew Davis, David Lobell, and Stefano Ermon. Combining satellite imagery and machine learning to predict poverty. *Science*, 353(6301):790–794, 2016.

[4] Sang Michael Xie, Neal Jean, Marshall Burke, David B. Lobell, and Stefano Ermon. Transfer learning from deep features for remote sensing and poverty mapping. In *AAAI*, 2016.

[5] Caleb Robinson, Fred Hohman, and Bistra N. Dilkina. A deep learning approach for population estimation from satellite imagery. *CoRR*, abs/1708.09086, 2017.

[6] Anna X. Wang, Caelin Tran, Nikhil Desai, David Lobell, and Stefano Ermon. Deep transfer learning for crop yield prediction with remote sensing data. In *Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, COMPASS ’18*, pages 50:1–50:5, New York, NY, USA, 2018. ACM.

[7] Mark EJ Newman. Modularity and community structure in networks. *Proceedings of the national academy of sciences*, 103(23):8577–8582, 2006.

[8] Kartikeya Bhardwaj and Radu Marculescu. Dimensionality reduction via community detection in small sample datasets. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 102–114. Springer, 2018.

[9] NOAA. Monthly Nightlight Satellite Imagery Dataset. [https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html](https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html) 2013. [Online; accessed 7-Sept-2018].

[10] The World Bank. Living Standards Measurement Study (LSMS) Dataset. [http://microdata.worldbank.org/index.php/catalog/lsms](http://microdata.worldbank.org/index.php/catalog/lsms) 2013. [Online; accessed 7-Sept-2018].