Beyond S-curves: Recurrent Neural Networks for Technology Forecasting

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Abstract

Because of the considerable heterogeneity and complexity of the technological landscape, building accurate models to forecast is a challenging endeavor. Due to their high prevalence in many complex systems, S-curves are a popular forecasting approach in previous work. However, their forecasting performance has not been directly compared to other technology forecasting approaches. Additionally, recent developments in time series forecasting that claim to improve forecasting accuracy are yet to be applied to technological development data. This work addresses both research gaps by comparing the forecasting performance of S-curves to a baseline and by developing an autencoder approach that employs recent advances in machine learning and time series forecasting. S-curves forecasts largely exhibit a mean average percentage error (MAPE) comparable to a simple ARIMA baseline. However, for a minority of emerging technologies, the MAPE increases by two magnitudes. Our autencoder approach improves the MAPE by 13.5% on average over the second-best result. It forecasts established technologies with the same accuracy as the other approaches. However, it is especially strong at forecasting emerging technologies with a mean MAPE 18% lower than the next best result. Our results imply that a simple ARIMA model is preferable over the S-curve for technology forecasting. Practitioners looking for more accurate forecasts should opt for the presented autencoder approach.

1 Introduction

In an environment where technological development largely determines economic growth and social change, predicting these developments is critical for strategic decisions in organizations [1]. Predicting technological development necessitates understanding and modeling it [2]. Once a model for technological development exists, one can use that model to forecast to aid strategic decisions [3] [4] [5]. The pay-off of having a model to forecast with sufficient accuracy is significant; however, constructing such models is difficult due to the considerable heterogeneity and the complexity of the technological landscape [6] [7] [8].

Successful innovations become gradually more adopted by the market and society. This diffusion is a gradual process that can be modeled by S-curves [9] [10], which have a long history and appear in many different domains, e.g., Biology [11]. S-curve segment development into three phases: introduction, growth, and maturation phases [12] [13]. They help explain past observed development behavior.

However, we find several pitfalls when using S-curves to forecast technological development. First, forecasting is the most useful for emerging technologies, i.e., in the Introduction phase of the S-curve. However, little data on the technology’s development is available in this phase. This poses problems for S-curve forecasting: accurate S-curve forecasts require more data, only available at a later life cycle stage where more of the technology’s development has been observed. However, at that point, the utility of forecasts is reduced, as most of the technology’s development has already happened. Second, to correctly
forecast using S-curves, practitioners must assume that the development will follow an S-curve pattern. To our knowledge, quantitative works have yet to empirically confirm that such an S-curve is eventually observed across all technology domains (especially not done in information technologies, which have a reduced or accelerated life cycle).

Recent developments in machine learning methods address these pitfalls. They can capture complex non-linear relationships between input and output indicators and are thus especially strong at finding patterns in large amounts of data [14]. They claim to improve forecasting capabilities by reducing the assumptions taken by finding patterns in the data in a supervised or unsupervised manner, i.e., they are data-driven.

The first of our two-fold contribution is an evaluation of the forecasting capabilities of the S-curve. We found a research gap in comparing the S-curve’s forecasting capabilities against baselines. To address this gap, we develop a practitioner’s guide to S-curve forecasting and compare the forecasts’ accuracy to an ARIMA baseline. We find that S-curves largely exhibit a similar forecasting accuracy to the ARIMA approach except for a small minority of emerging technologies, where the forecasting error increases.

The second of our two-fold contribution is a forecasting approach leveraging recurrent neural networks (RNNs) to forecast technological development. By using a modern data-driven approach, we aim to address the earlier described pitfalls of S-curves and to improve forecasting accuracy for technologies early in the life cycle. We apply a sequence-to-sequence model developed by Salinas et al. that forecasts product demand on Amazon to technological forecasting [15]. This approach improves out-of-sample mean average percentage error (MAPE) by 14% on average and by 12% (median) for emerging technologies over the next best result.

Our data source for this work is arXiv, a platform that provides access to more than two million scholarly works in over 170 technical domains. Most previous work uses patents as their data source, as a direct link between patents and economic value has been shown [16] [17]. Previous work has established strong links between scholarly works and patents [18] [19] [20], and scholarly articles predate patents by four to five years [21]. Thus, we use arXiv as our data source to forecast trends at an earlier stage than would be possible by using patents.

We structure the remainder of this article as follows. In Section 2 we justify using scholarly works to forecast technological development in previous work and then give an overview of related forecasting approaches. Section 3 presents our dataset and how we produce comparable forecasts with the forecasting approaches we evaluate in this work. In Section 4, we present our results, give an interpretation, and discuss them. Lastly, in Section 5 we conclude our work and give future research directions.

2 Related Work

2.1 Scientific Publications as a Datasource

Related work in the technology forecasting domain generally uses technological texts, e.g., books or scholarly articles, as data sources. Patents and scholarly articles have proven popular among researchers. Therefore, in the following section, we critically analyze both and explain why we choose scholarly articles as our data source.

In [22], the authors compare multiple data sources in their predictive value in the Green Energy domain. They find that patents and academic articles contribute the most trends of the data sources analyzed. Martino [23] classifies data sources along the innovation life cycle. According to the author, basic and applied research can best be forecasted using scientific publications, while the development of specific technologies is best reflected in patents.

For these reasons, a large part of previous research uses patents as their primary data source. A patent is an intellectual property that gives specific rights to the patent holder. Patents are a direct output of R&D activities of companies and individuals and can thus be seen as a direct measure of technical innovation [23]. Previous research has shown a direct link between patents and economic value [16]. Furthermore, patents protect intellectual property from being copied. Protecting shows direct economic interest in using the intellectual property protected by the patent [17]. The direct link between patents and value and the fact that patent data is readily available in patent databases makes patents a popular choice for technological forecasting.

Establishing a direct link between economic value and basic research is more challenging. So the main question is: why use scientific publications as a data source in technological forecasting? The two main
reasons are the scientific publications’ strong influence on patents and the lead time between publications
and patents [21].

Previous work has shown strong links between publications and patents: the number of cited scientific
articles in patents is increasing [25], technology development is heavily influenced by public research [26],
increasingly patents get published by the same entities that publish scientific articles [17], and the
countries with the highest number of publications are also the countries with the highest number of patents [27]. Therefore, we conclude that research activity and patenting activity are heavily linked.

Additionally, publications lead patent trends. The authors of [21] aim to quantify forecasting lead
times of different data sources by comparing patents and scientific articles to discover which source first
signals technology trends. They find that trends can be identified the earliest in scientific articles, four
to five years in advance of patents, and nine years in advance of web searches and news articles. The
fact that trends in scientific articles predate trends in patents indicates that articles can be seen as a
precursor to patents.

Therefore, by using scientific publications as our dataset, we are forecasting trends at an earlier stage
than would be possible by using patents, and we are forecasting the same trends.

2.2 Quantifying Technological Development

We can segment previous approaches to quantifying technological development into quantitative [28] [29]
and qualitative approaches [30]. Qualitative approaches rely on expert opinion to interpret the current
technology landscape and forecast. Relevant to this work are quantitative approaches, which we divide
into two main clusters: direct measures and indirect measures. We structure and justify the remainder
of this subsection along these clusters.

Researchers use performance metrics of technologies to directly quantify technological progress, e.g.,
cost per unit, power output, efficiency, or energy consumption. The improvement in a metric (e.g.,
decrease in cost per unit) is then equated with technological development. In [31], the authors forecast
the future cost of green energy solutions. Depending on the future decrease, they present several scenarios,
with lower costs leading to higher adoption. In [32], the authors use drilling costs and oil and gas outputs
to analyze the oil and gas industry change. In [33], the authors create a database of performance metrics
for information technologies and structure the metrics across three dimensions: storage, transformation,
and transport. In [34], the authors build on the previously presented work and forecast 28 technological
domains using performance metrics on storage-, transformation-, and transport capabilities. The main
advantage of using performance metrics to forecast is the direct measurement of technological progress
with measurable impact. However, using direct measures also has its problems: gathering long-term
performance data can be difficult, and only a subset of technologies where performance data exists can
be forecasted.

To fill this gap, previous work also uses indirect measures to quantify technological progress. Indirect
measures are proxies for the indirect effects of technological progress. Often, indirect measuremen
is done via bibliographic metrics, such as count data and citations. The idea behind using these metrics is
that technological progress is reflected in technological texts. Thus, the underlying assumption is that
progress can be proxied by the activity in technological texts measured by bibliometrics.

Previous citation analysis work mainly focuses on using patents as the data source. These works
mainly do citation analysis to attribute a measure of value to patents, e.g., highly cited patents indicating
a valuable patent [35]. In [36], the authors build a patent citation network to understand the structure
of the organic photovoltaic domain. In [37], the authors evaluate the blockchain and Internet of Things
landscape using patent citation analysis; in [3], the authors build an evolution path of the lithium iron
phosphate battery using a citation network built from academic articles. In [38], the authors build a
citation network from academic articles and patents to conduct a gap analysis between them.

Besides citations, the number of scientific publications is an important metric to gauge activity in a
technology field [39]; thus, the earliest technology forecasting work analyzes document counts [9], [10].
More recent examples are [12], [40], and [41]. The uptick of publications in a patent cluster indicates
discoveries and technological progress. Using document counts has two major drawbacks. First, the
count depends heavily on the underlying document taxonomy, i.e., how documents are assigned to tech-
nologies [24]. An inaccurate taxonomy, where documents are misclassified, wrongly defines technologies
and, thus, wrongly counts documents. Second, counting documents equally does not reflect the fact
that only a minority of documents accounts for the majority of the added value [16]. A nominal count
wrongly equals document contributions.

The choice of academic articles as our data source excludes individual article analysis to forecast
technologies. A link between individual scientific articles and economic value is difficult to establish since research predates technology diffusion by multiple years. For example, a high citation count of academic articles does not necessarily translate to high economic value later [42]. Thus, doing citation analysis on individual academic articles for technology forecasting has less utility. Since analyzing document counts is an established technique in the technology forecasting domain, we use the count of published articles as a proxy for technological development.

2.3 Previous Forecasting Approaches

For our literature review, we divide related work focusing on forecasting indirect development metrics into two main approaches: model-based and data-driven approaches. We structure the remaining paragraphs along these main approaches.

Technological development is the invention, innovation, and diffusion of new technologies, i.e., novel processes that produce outputs that were not feasible before [43]. An invention constitutes a scientifically or technologically new product or process, which may or may not develop into an innovation, which happens when an invention is commercialized [43]. A successful innovation becomes gradually more adopted by the market and society. Model-based approaches generally assume a life cycle model that explains the technological development in the past, i.e., they are theory-driven. Multiple model-based approaches exist; a popular one is the S-curve. S-curves have a long history and appear in many different domains, e.g., Biology [11].

Figure 1: S-curve of technological development. The y-axis represents a technology-performance indicator which captures the technological development over time (x-axis). Examples of performance indicators are adoption rate or the number of news articles published on a technology [41].

S-curves model the life-cycle of technological development through three distinct phases [12], [13]: the Introduction-, Growth-, and Maturity phases. In the Introduction phase, an innovation is new on the market and adopted by relatively few users. It typically serves niche use cases, and changes to the technology happen slowly. The technology is further developed during the Growth phase and expands to mainstream use cases. The technology has become an attractive target for investment and adoption; thus, the rate of technological development and adoption increase exponentially as the market punishes players for not using more efficacious and efficient technologies. The technology approaches performance bottlenecks and other constraints in the Maturity phase. A technology stays at the Maturity phase until another innovation replaces it or new features allowing further development are added [44].

S-curves have been found to appear in many different technological domains. Meyer models the number of nuclear explosions, the population of Japan, the cumulative number of U.S. universities, and the adoption of electric generators using S-curves on time series data [45], [44]. Kucharavy and De Guio model energy consumption and infrastructure development as S-curves [46]. Andersen [47] shows the prevalence of S-curves in 56 technological groups, ranging from chemicals to non-industrial fields. Adamuthe et al., Priestly et al., and Pereia et al. show the prevalence of S-curves in computer-science-related fields [48], [12], [41].

Apart from using S-curves to explain past behavior, related work also uses them to forecast. In [46], the authors introduce a forecast segmentation. They segment forecasts into short-, medium-, and long-term forecasts depending on how far into the future forecasts are to be made. In [13], the authors focus on
short-term forecasts (10-20% of the existing data points), in \cite{40}, the authors fit S-curves on the number of patents in biped robot walking to find inflection points and saturation times and to do long-term forecasts on future trends for walking robots. In \cite{49}, Daim et al. present a forecasting approach that uses S-curves fitted on the number of patent publications in three technologies.

The presented works show one major advantage of model-driven approaches: typically, models have interpretable parameters, e.g., in the case of S-curves, the inflection point where the growth rate starts to slow down.

One major disadvantage of model-based approaches is the limited usability of model-based forecasts. When limited data is available (only the beginning of the S-curve), uncertainties in fits are high; thus, the utility of the fitted model is low. If more data is available (S-curve is advanced a lot), the certainty of fit is high. However, the utility for forecasting is also low, as most of the development has already happened \cite{50}. This is limiting since accurate forecasts are especially useful in the early development phase of a new technology \cite{12, 51}. Additionally, model-driven approaches assume an underlying growth model, e.g., the S-curve model in the case of the presented work. Forecasting accuracy reduces significantly if the assumption is wrong.

The recent successes of Machine Learning have led to waves of adoption in different domains, technological forecasting included. These machine learning approaches can capture complex non-linear relationships between input and output indicators and are thus especially strong at finding patterns in large amounts of data. They promise to tackle the disadvantages presented in the previous paragraph as they reduce the assumptions taken by finding patterns in the data in a supervised or unsupervised manner, i.e., they are data-driven.

As the direct economic value of single patents has been shown, most works employ data-driven methods to improve citation analysis. Several works divide patents into emerging technologies and not emerging and train a model to classify patents into these two clusters correctly. Whether a technology is emerging can be quantified using patent indicators such as forward and backward citations. In \cite{52, 53, 51}, the authors segment patents into emerging and not emerging and then train a machine learning classifier to identify patents with future potential correctly. In \cite{54}, the authors exploit the fact that the lifetime of a patent has been shown to be directly linked with economic value. They use a machine learning model to predict the probability that a patent will survive until its maximum expiration date. Other works use scholarly articles as their data source. For example, in \cite{55}, the authors classify important articles by their citation count. The work of Lee et al. \cite{56} combines a model-based with a data-driven approach: the authors use a machine learning model to predict the model parameters of a life cycle model.

A first research gap we see is a direct comparison of model-based approaches to other forecasting approaches. Even though model-based approaches are frequently used to generate forecasts, they have not been compared to other forecasting methods. Therefore, our work offers a critical analysis of their forecasting capabilities by comparing them to two other approaches.

While there is ample previous work on using machine learning approaches to forecast the value of individual patents, we find a second research gap in using machine learning approaches to forecast time series of technological development data. As shown, model-based approaches produce forecasts making assumptions that can be wrong. These assumptions can prove especially hard to make at the start of a time series, as insufficient time has passed for the time series to reveal its properties. Machine learning has proven itself useful for forecasting in this setting. Neural networks have achieved impressive results in sequence forecasting tasks, for example, in natural language processing (NLP) \cite{57, 58}. An architecture that has proven to be especially suited to sequential tasks is the recurrent neural network (RNN). RNNs model the sequential nature of data explicitly in contrast to other architectures; for more details, see \cite{59}. RNNs have recently been successfully applied to time series forecasting; see \cite{60, 61}. Especially interesting work is the one of Salinas et al. \cite{15}, who present a probabilistic sequence to sequence (seq2-seq) time series model that forecasts the demand of products on Amazon using RNNs. Their approach produces more accurate forecasts than baseline methods with interpretable confidence intervals for their forecasts. However, the model has yet to be applied to technological development data.

To fill the first research gap, we compare the S-curve’s forecasting performance to two forecasting approaches: ARIMA models and the data-driven approach we develop in this work. We test S-curves as a model-based forecasting approach because of their widespread presence in technological development data and ARIMA models because of their widespread and easy use.

To address the second research gap, we develop a data-driven forecasting approach based on the work of Salinas et al. \cite{15} to predict the number of scholarly publications in technological fields. We focus on applying their model architecture to technological development data from \texttt{arXiv} data to forecast.
3 Data and Methods

In this section, we first introduce the dataset we use in this work and how we construct an empirical variable acting as the technology performance indicator (TPI) we are forecasting. Afterward, we explain how we generate technology forecasts using S-curves, ARIMA models, and Salinas’ time series forecasting approach and how we evaluate their performance.

3.1 Data

In this work, we use arXiv as our dataset, an open-access distribution service created in 1991 of more than two million scholarly articles related to more than 170 technical domains. It is openly available for download and comprises more than 3 TB of .pdf files of scientific texts and their associated metadata [62]. We use the e-prints uploaded to the arXiv as the data source because they represent an exhaustive body of knowledge in many technical fields.

arXiv organizes publications into eight main categories and provides a definition of its taxonomy [2]. The main categories are Computer Science, Economics, Electrical Engineering and Systems Science, Mathematics, Physics, Quantitative Biology, Quantitative Finance, and Statistics. These main categories further break down into 170+ subcategories. The taxonomy of Computer Science fields is based on the ACM Computing Classification System and distinguishes between 40 different subfields. The taxonomy of the other main categories is explicitly defined by arXiv on their website. Researchers classify their e-prints when uploading them. Moderators then check the classification. We assume the classification to be robust because the taxonomy was reached through consensus by a board of experts, researchers have the incentive to classify their research correctly, and moderators check the classification [41]. We assume each subcategory on arXiv to form an exclusive and exhaustive body of knowledge representing different technologies. Therefore, in the subsequent text, when referring to a subcategory, we refer to the technologies it represents.

The metric we use to quantify technological development is the number of e-print uploads to arXiv. This number is a proxy for the development of the technologies described in the e-prints. We calculate this metric monthly to balance the velocity and the amount of data (yearly aggregation yields too few data points and aggregates too much, and daily aggregation yields a time series with high variance). This produces one time-series $z_i$ of the number of e-prints uploaded per month for each subcategory on arXiv, cf. Figure 2. We exclude some subcategories, as their time series are too short, yielding 148 time series.

Figure 2: Monthly e-print count for selected subcategories on arxiv. cs.LG, math-ph, and q-fin.TR designate the Computer Science Machine Learning, the Mathematical Physics, and the Quantitative Finance Trading and Market Microstructure subcategories, respectively. The three subcategories show different development patterns and are not stationary.

[https://arxiv.org/category_taxonomy](https://arxiv.org/category_taxonomy)
3.2 Methods

In the following subsection, we explain how we develop a model-driven and a data-driven technology forecasting approach and how we compare their performance. We show how we produce forecasts on the arXiv data using S-curves as our model-driven approach and ARIMA as our baseline. Additionally, we apply Salinas’ et al. [15] model to technology forecasting and evaluate its capabilities on technology forecasting data. Therefore, we detail how we implement their model, train it, and forecast with it.

3.2.1 S-curve

To produce S-curve forecasts as practitioners would do, we create two types of forecasting windows to simulate technologies in different stages in their life cycle, cf. Figure 3. The first window type simulates technologies early in their life cycle, where only little data is available. We refer to these windows as emerging technology windows or simply emerging windows. These windows contain the first third of a given time series. The second window type simulates technologies later in their life cycle. We refer to these windows as established technology windows, or established windows. The established windows contain the first two-thirds of a time series. Applying this procedure to the 148 time series in our dataset, we get 296 windows, one early life cycle, and one late life cycle window for each time series. For both types of windows, we produce three-year forecasts. We fit the S-curve formulation onto the available data for each window using a non-linear fitting procedure. The fitting requires hyperparameters to constrain the parameters of the S-curve. We conduct a grid search for each window to find the hyperparameters that yield the most accurate fit. After calculating an S-curve fit on every window, we produce forecasts by calculating the number of uploaded papers for a technology as given by the S-curve and compare that to the observed number of uploads by calculating the RMSE and MAPE. In the following, we refer to forecasting using S-curves as the FIT approach.

![Figure 3: We evaluate the forecasting approaches at two stages in the subcategory life cycle. The emerging technology windows contain the first third of a given time series and are then used by a given forecasting approach to forecast the subsequent three years. The established technology windows consist of two-thirds of a time series. Applying this transformation to the 148 time series in our dataset yields 296 forecasting windows.](image)

3.2.2 ARIMA

To introduce a baseline, we directly compare the FIT forecasts to forecasts produced by ARIMA models. ARIMA models are state-of-the-art and widely used to forecast time series. We use the same windows we created for the FIT forecasts. All models are ARIMA(1, 0, 1) models; any other configuration caused convergence problems due to some time series in our dataset being too short for larger orders. However, that does not pose problems, as we use the ARIMA models only as a baseline to compare against. Here again, we produce a three-year forecast and calculate RMSE and MAPE.

3.2.3 RNN

Forecasting using S-curves and ARIMA models is fundamentally different from forecasting with the RNN model. With S-curves and ARIMA models, we fit a different forecasting model to every window, whereas the RNN model trains on all time series simultaneously to create one forecasting model.
Figure 4: Dataset augmentation technique we use to create training samples \[15\]. On the left, we show how we generate multiple training samples from one time series. We slide a fixed-length window over the time series to create the training samples. Thus, we can create multiple training samples from one time series. In the example above, we create four training samples. The right graph shows the structure of one training sample. The vertical line splits the window into the conditioning range \((1, \ldots, k)\) and the prediction range \((k + 1, \ldots, T)\).

such, we have to present the RNN forecasting approach differently. To present it, we distinguish between implementation, training, and evaluation. First, we present how we implement Salinas’ model to forecast technological development on our arXiv dataset. Second, we go into detail about how we train the model. Third and last, we explain how we evaluate the model and compare its performance to the FIT and ARIMA approaches.

Sequence-to-sequence (seq-2-seq) models like the one Salinas et al. developed, are powerful at modeling the sequential nature of data. They map an input sequence of arbitrary length to an output sequence of arbitrary length. These models consist of two parts: an encoder and a decoder. The encoder encodes the input time series \(z_i\) into a hidden state \(h_i\). The decoder decodes that hidden state into the output. The output depends on the hidden state; thus, on the input, i.e., the decoder is conditioned on the input \(z_i\). Both the encoder and decoder are trained in parallel to map an input to the desired output as accurately as possible.

We augment the dataset by generating multiple training samples from each time series, cf. Figure 4a.

We divide a training sample into a conditioning range and prediction range. During the training, the model forecasts the values in the prediction range using the conditioning range as input. The forecasted values are then compared to the observed values in the prediction range, and the error is backpropagated to train the model weights. During testing, only values in the conditioning range are available. To ensure comparability with the previous two forecasting approaches, we set the length of the prediction range to 36 months, i.e., three years. Choosing the length of the conditioning range is a trade-off between the number of training samples and forecasting accuracy. Increasing the conditioning range increases forecasting accuracy and decreases the number of training samples. We set the length of the conditioning range to 36 months, or three years, to strike a balanced trade-off. In total, each training window is six years long.

To generate a training sample, we slide a window of fixed-length \(l\) from the beginning \(t_1\) of the time series to the end, where each starting date marks a new training sample. This technique generates multiple training samples of the same length \(l\) from each time series. Our data set comprises 148 distinct time series, from which we generate around 13 000 training samples.

The number of e-prints uploaded on arXiv varies from subcategory to subcategory; thus, each time series has a different scale. Figure 5 shows the unequal distribution of papers between the subcategories on arXiv. Without scaling, the model would have to learn to scale appropriately on top of forecasting, yielding worse accuracy and convergence. In these cases, it is standard practice to scale the affected variables. In this work, we scale a training sample by the mean value of the time-series \(z_i\) in the conditioning range \[15\]

\[
\text{scaled} = \frac{z}{\bar{z}} \quad \text{with} \quad \bar{z} = 1 + \frac{1}{k} \sum_{t=1}^{k} z_{i,t}.
\]

To predict the development of a subcategory from beginning to the end, we split the data set across the subcategories into training-, validation-, and test set. We randomly choose 10% of sections to be in the validation- and test set, all training samples generated from these subcategories are never seen during
training. If we took the beginning of each time series as our training set and the end as our validation- and test set, the training and evaluation would be biased: during training, the model would never see samples from the end of a time series. Conversely, during testing, the models would never be evaluated for predicting the beginning of a time series. Therefore, by choosing whole subcategories as the test set, we can evaluate the model’s forecasting capabilities along the whole life cycle of technologies.

We conduct a hyperparameter search to find the best training parameters and the most accurate model configuration. We vary the models across two dimensions: the model type (RNN vs. LSTM), and the model complexity (number of hidden nodes). It is standard practice in Deep Learning to vary the model complexity and model type to find the simplest model structure that can still forecast accurately. We determined the training parameters in a previous hyperparameter search. To train the model, we use a batch size of 64, a learning rate of $0.001$, and 750 training epochs.

For the evaluation of the RNN approach, we use the forecasting windows shown in Figure 3. Reusing the same windows used to evaluate the two previous forecasting approaches permits an unbiased comparison. However, we cannot use all evaluation windows because they contain the RNN training set windows. We only use forecasting windows from subcategories in the RNN test set to avoid false accuracy metrics to evaluate the RNN’s accuracy.

### 4 Results and Discussion

| Method  | RMSE mean/median | MAPE mean/median |
|---------|------------------|------------------|
| FIT     | 64.3/9.0         | 984.8/36.3       |
| ARIMA   | 18.7/8.2         | 49.6/38.2        |

(a) Forecasting accuracy for the FIT and ARIMA methods on all 148 technologies. Both approaches forecast with similar accuracy in the median; however, due to outlier predictions the mean accuracy metrics for the FIT approaches are significantly larger compared to the ARIMA approach.

| Method  | RMSE mean/median | MAPE mean/median |
|---------|------------------|------------------|
| FIT     | 249.3/11.6       | 2955.8/36.2      |
| ARIMA   | 19.0/8.8         | 55.0/33.7        |
| RNN     | 14.1/9.4         | 41.5/32.5        |

(b) Forecasting accuracy for the FIT, ARIMA, and RNN methods on the test technologies. The RNN approach produces the most accurate forecasts.

Table 1: The mean and median forecasting accuracy for the FIT, ARIMA, and RNN methods. We include mean and median as the forecasting errors are right-skewed and highlight the lowest score in each column in bold.

Comparing the performance of the FIT and ARIMA models, cf. Table 1a we see that the FIT approach exhibits one magnitude higher mean error metrics and that the error distributions are right-skewed. The FIT approach has a mean MAPE of 985% versus the ARIMA approach, which has a mean
MAPE of 50%. However, the median error metrics are similar (the largest difference is 1.9%), around 37%. We trace this behavior to outlier forecasts of the FIT approach. On a minority of windows, the FIT approach forecasts very poorly.

The poor performance of the FIT approach is caused by its tendency to forecast exponential growth phases for windows where the S-curve’s growth phase has yet to happen. Looking at Figure 6, we see that the fitting procedure fits the S-curve well to the observed data. However, since no growth happened, the fitting procedure can exploit that fact by putting the beginning of an exponential growth phase at the end of the observed data. This reduces the in-sample fit error but produces erroneous forecasts.

Figure 6: Qualitative comparison of forecasts produced by each approach. While the forecasts of the ARIMA and RNN approaches are close, the FIT approach forecasts a false growth spurt. We attribute this behavior to the fact that the fitting algorithm needs to fit a growth spurt to data where no real growth has occurred. The fitting algorithm exploits this to reduce the fitting error by putting an exponential growth phase at the end of the observed data.

The tendency of the FIT approach to forecast erroneous growth spurts is due to the assumption that the development follows an S-curve pattern. The S-curve formulation includes a growth spurt. If a given observed life cycle does not exhibit a growth spurt, an S-curve will not accurately describe the development. The main problem is that at the beginning of a technology’s life cycle, practitioners cannot know which life cycle model a technology will follow. This shows the central crux of using life cycle models: to produce useful forecasts, practitioners need to forecast technologies as early as possible without having enough information to make correct assumptions.

Comparing the RNN approach to the previous two approaches, cf. Table 1b, we see that the RNN approach produces the most accurate forecasts on average. Its MAPE is at 41.5% on average, 13.5% lower than the next best result, the ARIMA approach. The ARIMA model has the second-best mean MAPE of 55%. However, its median MAPE at 33.7% is only 1.2% higher than the RNN’s median MAPE, indicating a more pronounced right-skew. Again all error distributions are right-skewed, with the FIT approach exhibiting the lowest accuracy and the heaviest right-skew. Its mean MAPE of 2955.8% is two magnitudes higher, while its median MAPE at 36.2% is only 2.5% higher compared to the next best result.

The biggest difference in MAPE between ARIMA and the RNN approaches comes from windows where the ARIMA model predicts accelerating growth. Although growth is slowing, the RNN predicts the slowing growth correctly, cf. Figure 7. The ARIMA model’s formulation cannot capture the reversing trend in these cases. It predicts an accelerating growth if the growth was accelerating in-sample.

Figure 7: Qualitative comparison of forecasts produced by each approach. The ARIMA approach predicts the accelerating trend to continue, while the RNN approach captures the reversing trend.

All forecasting methods forecast the established windows more accurately than the emerging windows, cf. Figure 8 and Table 2. The median and mean MAPEs for the established windows are, without exception, lower than the emerging window MAPEs for every method. The emerging window median MAPEs are 20.1%, 24.8%, and 6.7% higher than the established window MAPEs for the FIT, ARIMA, and RNN approaches, respectively. However, we observe that the RNN forecasts the emerging windows the most accurately of all approaches with a mean MAPE of 42.6%. The ARIMA approach achieves the
next best MAPE of 60.2%. Therefore, we conclude that the performance advantage of the RNN approach comes from its ability to forecast emerging technologies more accurately than the other approaches.

Table 2: The mean and median forecasting accuracy for the FIT, ARIMA, and RNN methods drilled down by the window type. Emerging windows represent the first third of a technology's life cycle, and established windows represent the first two-thirds. While all models predict established windows with similar accuracy, the RNN approach predicts emerging windows (which are important for practitioners) 18% more accurately on average than the next best approach.

(a) Forecasting accuracies on the emerging windows.

(b) Forecasting accuracies on the established windows.

![Boxplots visualizing the MAPE accuracy distribution for each forecasting approach drilled down by window type. All models predict established windows with similar accuracy; the RNN approach predicts emerging windows more accurately than any other approach.]

Figure 8

5 Conclusion

Even though S-curves and other technological development models have been used extensively to forecast, our literature review revealed a research gap in their direct evaluation against other established forecasting methods. Additionally, model-based approaches suffer from one major pitfall: their forecasts require sufficient data to produce accurate forecasts. However, the most benefit can be had when forecasting emerging technologies, for which sufficient data is usually not available. We identify a second research gap in applying modern machine learning-based, data-driven forecasting approaches to tackle these issues.

To address the two presented research gaps, we develop a practitioners guide on producing forecasts using S-curves and benchmark their performance against ARIMA forecasts. Additionally, we apply a probabilistic time series forecasting approach developed by Salinas et al. [15] to technological development data and compare its performance to the previous two forecasting approaches.

We find that the S-curve and ARIMA approaches have comparable median forecast accuracies. However, in a minority of samples, the S-curve forecasts erroneous growth spurts on new technologies, which increases the mean forecasting errors by two magnitudes over the ARIMA approach. The RNN approach forecasts established windows with the same accuracy as the two previous approaches but emerging windows with a mean MAPE 18% lower than the next best result.

Our findings have a significant implication for practitioners looking to employ S-curves or other model-based approaches to forecast technologies. S-curves have been proven to be useful in explaining past development. However, our work casts doubts on their utility in producing useful and accurate forecasts. Practitioners using a quantitative forecasting approach should consider using a simple ARIMA model to
forecast over S-curves, as it has proven to be more accurate for emerging technology prediction and as accurate as S-curve predictions for established technologies.

The RNN approach we present in this work is promising thanks to its accurate forecasts, but it is more complex to implement. We advise practitioners looking for quick estimating forecasts to employ a simple ARIMA model. Practitioners seeking more accurate forecasts, especially on emerging technologies, should opt for the RNN approach.

We see further venues to improve the forecasting accuracy of the RNN approach by finding and testing other predictive features. In our work, the RNN model only used the previous count as a feature. One approach could be to use the semantic information captured in texts. Embeddings are an established way to capture the semantics of texts ([63], [64]) and have been shown to improve the forecasting accuracy of a wide range of forecasting tasks [65]. Embeddings pre-trained on scientific texts [66] could be employed to render textual semantic information digestible to this work’s model and improve forecasting accuracy.

Furthermore, future work could evaluate the presented approach on other datasets. arXiv is only one of multiple publication platforms. Augmenting the arXiv with data from other platforms might improve the inference of the model, as the model now has more training samples to learn patterns from.

Additionally, future work can change the taxonomy and thus get more fine-grained resolution on technologies. As shown in the literature review, the taxonomy strongly influences the performance of count-based forecasting approaches. We assumed the 148 evaluated arXiv subcategories to be distinct areas of knowledge. Nevertheless, some subcategories contain multiple topics and are very exhaustive (e.g., cs.LG), while others are more specialized subcategories. In extensive subcategories, averaging effects might take place that hide development patterns. A different, data-driven taxonomy might uncover interesting areas of knowledge and disaggregate development patterns, allowing the model to learn and use them to forecast. One recently published dataset that provides a data-driven taxonomy is OpenAlex. Its taxonomy encompasses 65,000 so-called concepts organized in a directed-acyclic graph. Concepts are abstract ideas that scholarly works discuss. In OpenAlex, every scholarly work is tagged with multiple of these concepts. Future work could investigate if a more fine-grained taxonomy improves the forecasting accuracy of the RNN approach.

[https://docs.openalex.org/](https://docs.openalex.org/)
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