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Methodological Review

Generative adversarial networks for biomedical time series forecasting and imputation

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ABSTRACT

In the present systematic review we identified and summarised current research activities in the field of time series forecasting and imputation with the help of generative adversarial networks (GANs). We differentiate between *imputation* which describes the filling of missing values at intermediate steps and *forecasting* defining the prediction of future values. Especially the utilisation of such methods in the biomedical domain was to be investigated. To this end, 1057 publications were identified with the help of PubMed, Web of Science and Scopus. All studies that describe the use of GANs for the imputation/forecasting of time series were included irrespective of the application domain. Finally, 33 records were identified as eligible and grouped according to the topologies, losses, inputs and outputs of the presented GANs. In combination with a summary of all described application domains, this grouping served as a basis for analysing the peculiarities of the method in the biomedical context. Due to the broad spectrum of biomedical research, nearly all recognised methodologies are also applied in this domain. We could not identify any approach that proved itself superior in the biomedical area. Although GANs were initially designed to work in the image domain, many publications show that they are capable of imputing/forecasting non-visual time series.

1. Introduction

Time series data accrue in many medical contexts. First of all, bedside monitors gather patient-related time series data like vital signs, EEG waves and alike. Moreover, hospital logistics and stock management depend on temporal inventory data as well as on information regarding seasonal trends and resource utilisations in different clinics. Thus, accurate forecasts and imputations can help to improve patient care in several ways and are of great importance to different stakeholders in the medical field. Besides sequence-to-sequence models based on recurrent neural networks (RNN) or transformers, generative adversarial networks (GAN) have been suggested to compute such infills or predictions. The present review summarises the current state of published research with regard to GANs utilised for forecasting or imputing time series data.

GANs consist of two opposing neural networks competing in a minimax game [1]. One network, the generator, tries to produce samples according to a distribution that is as similar as possible to the underlying real distribution. In the original version, the generator is only fed with noise as input. The second network, the discriminator or critic, learns to differentiate between samples from the real distribution and the ones created by the generator. The decision of the critic serves as a basis for the generator's error. After training, unusually only the generator is used. The original application domain for GANs was the synthetic image generation.

For conditional GANs, additional inputs are handed to the generator (and the critic) which serve as the conditioning facts for the learned distribution. In the image generation domain, such information could be the desired content of the synthesised image.

The aim of our work was to identify and group GAN-based approaches and concepts as well as their application domains. The focus lay on biomedical applications, but publications in other fields were also considered to form a comprehensive overview. Moreover, persisting shortcomings and open research questions were to be identified. To this end, we loosely followed the reporting guidelines of the PRISMA 2020 statement [2].

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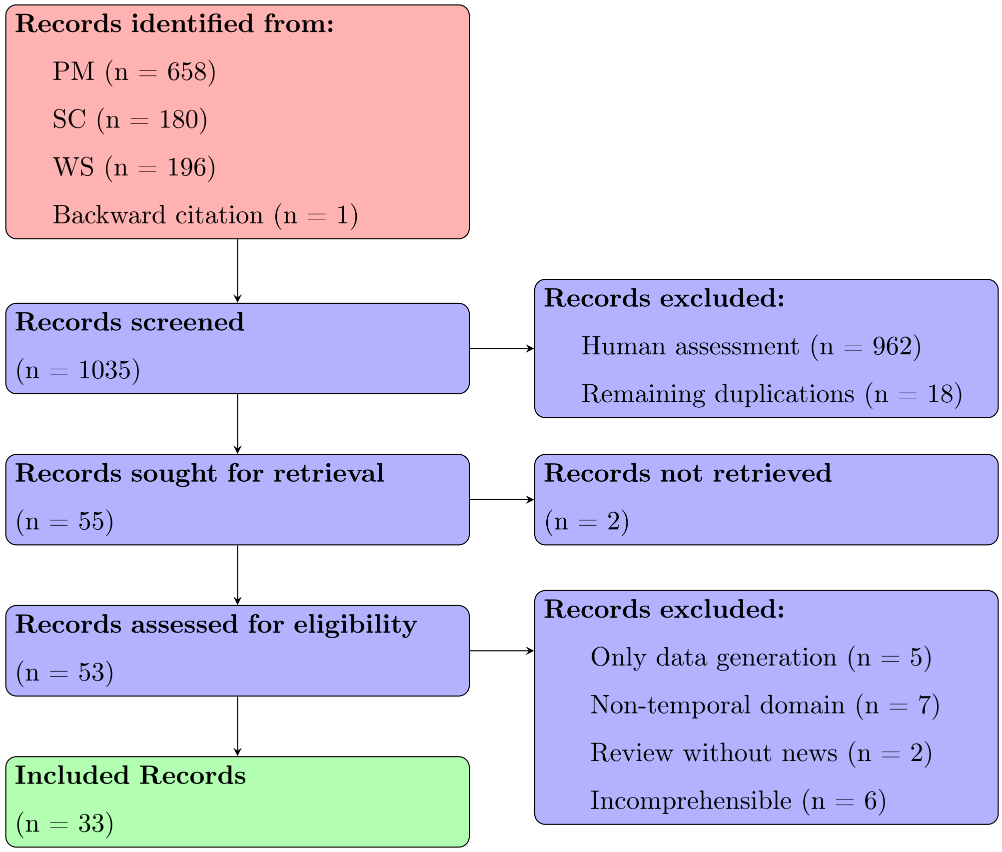

Fig. 1. Systematic process of identifying suitable publications that are included in the present review. PM: PubMed, SC: Scopus, WS: Web of Science.

2. Methods

Studies on time series forecast or imputation with the help of GANs were included in the report. Besides articles about systems specialised for the medical domain, papers of other domains were also included. The review was not limited to publications regarding single GAN models or a specific GAN version. However, the works had to describe a concept for forecasting/imputing time series values. More precisely, studies that only consider methods for synthesising full time series that cannot be used for filling in missing values at intermediate steps (imputation) or at the end (forecasting) were excluded from the review. As GANs were introduced by Goodfellow et al. [1] in 2014, all studies published before that year were excluded. Furthermore, publications had to be written in English and to be available online. We searched MEDLINE, PubMed Central and Bookshelf with the help of PubMed. Moreover, the Scopus and the Web of Science platforms were used to identify publicly available articles on the topic.

On April 20th 2021 the first three databases were searched via the PubMed[1] (PM) interface with the following query: *((“generative adversarial network” [Title/Abstract] AND “time”[Title/Abstract]) OR (“GAN”[Title/Abstract] AND “time”[Title/Abstract])) AND (“2014”[Date - Publication]: “3000”[Date - Publication])*. In total, 658 results were found. The Scopus[2] (SC) search produced 180 results when queried with *(TITLE-ABS (“generative adversarial network”) AND TITLE-ABS (“time series”)) OR (TITLE-ABS (“GAN”) AND TITLE-ABS (“time series”)) AND PUBYEAR* $>$ *2014* on 30th April 2021. At last, the Web of Science Core Collection was scanned via the Web of Science interface[3] (WS) on 3rd May 2021. The query *(((TS=(generative adversarial network) AND TS=(time series)) OR (TS=(GAN) AND TS=(time series))) AND DOP=(2014/2022))* led to 196 results. A summary of the full process regarding the identification of suitable publications is depicted in Fig. 1.

Table 1
Result of the first screening phase. The first column corresponds to the search frameworks in which the publications were found.

Framework	Publications
WS	[3–13]
SC	[14–24]
PM	[25–40]
SC and WS	[41–53]
PM and WS	[54]
PM, SC and WS	[55,56]

Due to the broad query, a large number of the reported studies did not meet the inclusion criteria and had to be discarded. The records were screened by one reviewer (SF), who checked the eligibility of every result based on title and/or abstract. In case of doubt, a record was carried over into the second evaluation phase. After the first screening phase, 19 (PM), 26 (SC) and 27 (WS) records (including duplications) remained.

Most discarded publications describe image generation or modification tasks without a temporal component or do not cover artificial neural networks at all (e.g. works on Gallium nitride, Global Asthma Network, GAN Gene, greater auricular nerve, Giant axonal neuropathy etc.). A summary of all retained publications in combination with the query frameworks that identified them can be found in Table 1. Unfortunately, the publications by Yang et al. [53] and Wong et al. [17] were neither available via the university library in Jena (Thüringer Universitäts- und Landesbibliothek Jena) nor via any cooperating university

[1] https://pubmed.ncbi.nlm.nih.gov/.
[2] https://www.scopus.com/.
[3] https://www.webofscience.com/wos/woscc/advanced-search.

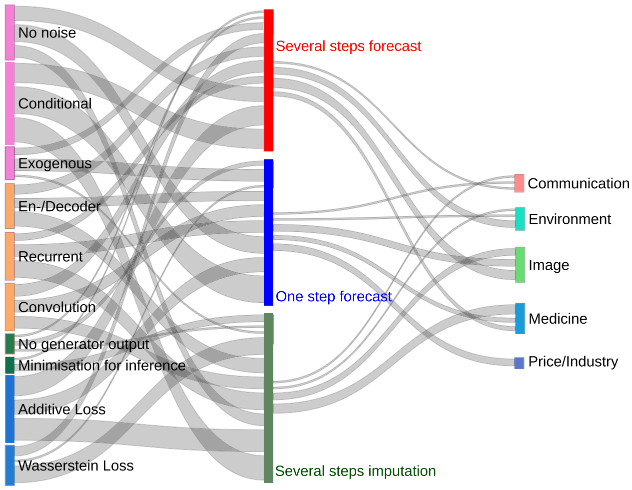

Fig. 2. Clusterings of the publications according to the methodologies (left), intended use cases (middle) and application domains (right) as well as their relationships.

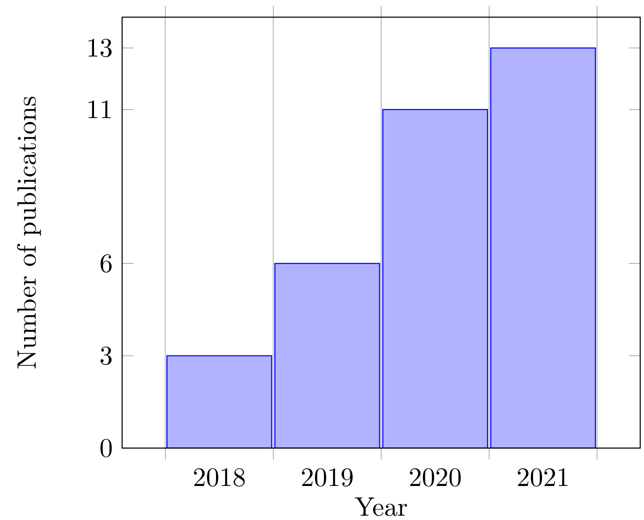

Fig. 3. Distribution of included records according to the year of their publication.

library in Germany. Thus, these papers were excluded from our review. In total, the search and screening phases led to 52 individual records. We did not find any published review regarding GAN-based approaches to time series imputation or forecasting, but a general review by Rizvi et al. on recent developments in the GAN domain [34]. During the in-depth analysis of all 52 publications, one more article was detected via a backward citation search. The work by Farajiparvar et al. [13] included a reference to the one by Zhang et al. [57] that we included as well. Appendix B contains a textual summary of all 53 publications including assessments regarding the advantages and limitations of the systems presented.

The information collection from the reports during the eligibility check was also conducted by SF. After the full review of all 53 publications, 33 were identified as matching our inclusion criteria. Five papers [14,18,23,6,24] only presented methods for the generation of fully synthetic training data. While this is a very useful application of GANs in the forecasting/imputation domain, it does not fit our research question. Another seven papers [54,30,31,33,36,16,27] were rejected as the presented methods are not directly applicable to the temporal inter- or extrapolation. The reviews by Rizvi et al. [34] was only used to verify that we did not miss any important publication regarding our question and was excluded before the information synthesis phase. Rizvi and colleagues identified 23 different application domains, of which *Market prediction and forecasting* and *Weather forecasting* overlap with the domains investigated in our review. The authors found 3 papers corresponding to these two topics, namely [55,14,22] which were also identified by us and one paper by Chen et al. [58] that we did not include in our review during the first phase. Although Rizvi et al. claim that the paper by Chen et al. includes a description of a weather forecasting mechanism, we could only find approaches for the generation of synthetic time series figuring the generation of renewable powers (wind/sun) over time.

The review by Farajiparvar et al. was also dropped after carefully investigating the works cited by the authors [13].

Furthermore, six articles [22,50,3,4,51,42] were excluded as the described methods and experiments were intransparent and thus, irreproducible. These 6 exclusions were audited by CS.

3. Synthesis of results

The present section is structured as follows. At first, we group all publications according to their methodologies and amplify these general ideas. Afterwards, we present the different application domains. A graphical representation of this grouping can be found in Fig. 2. Only the middle column depicts a disjoint clustering of all reviewed publications. The other two columns refer to groupings that allow the allotment of one work to multiple categories.

Fig. 3 depicts the distribution of the 33 included records according to the year of their publication. A tabular summary of the presented techniques, data sources, data set sizes, evaluation metrics and available code/data repositories for all of these publications is found in Table A.2.

3.1. Methodologies

The reviewed approaches can be grouped according to their inputs, topologies, outputs, and the losses to be minimised. These groups are detailed in the following and are represented in the first column of Fig. 2.

3.1.1. Inputs

We found 18 (55%) publications that describe GANs which do not use any random noise input. These systems only make use of historic and/or future values or utilise exogenous information for the forecasting/imputation of time series. Such deterministic approaches lead to the same infilling whenever the context information does not change [38,26,28,35,37,39,25,55,29,9,43,46,57,45,32,8,56,11,19].

Nearly all reviewed systems, namely 29 (88%), make use of conditional GANs. That means, the generators and in some cases also the discriminators use context information like historic/future values of the same series or extrinsic data. All approaches of the first group also belong to this one [38,26,28,19,35,37,39,10,20,49,40,25,p019515, 55,7,48,29,9,43,46,12,5,57,45,52,32,8,56,11].

Around 27% (9) of the reviewed models use other information as inputs than the historic or future values of the series that is to be infilled or predicted. They either add such exogenous context to the self-referential information or use it as the only source for the forecasting/imputation task [28,39,40,55,48,46,57,32,11].

3.1.2. Topologies

14 (42%) publications describe the implementation of a generator that consists of an encoder-decoder pair (e.g. image U-nets, autoencoders) [26,28,38,37,39,10,49,25,15,29,9,46,45,32].

Furthermore, 15 (45%) reviewed articles delineate the application of recurrent layers inside the generators. In most cases, variants that are specialised to learn long-term dependencies (long short-term memory cells or gated recurrent units) are used [37,26,10,44,49,40,21,15,7,48,43,46,57,45,11].

In 15 (45%) publications the usage of (de-) convolutional layers as generative building blocks is detailed. Not only images are processed this way, but also non-visual data like graphs [28,32,19,38,48,5,41,35,37,39,47,40,55,29,9].

3.1.3. Outputs

In most cases, the trained generator is used for the actual imputation or forecasting. However, we identified 4 systems that work slightly differently. They either only use parts of the trained generator [26], interpret the outputs as intermediate results which need further processing [10,12] or combine outputs of several GANs into a final one [43].

A few of the reviewed approaches (4,12%) solve a minimisation task during inference. Instead of computing only one prediction or infill for the missing parts, these systems compute several ones for the whole time series (including the already known steps). Afterwards, the noise input is searched for that leads to the smallest difference between the predicted values of the established steps and their real counterparts. The predictions created by the minimising noise input are then used as the final result [41,47,21,52].

3.1.4. Losses

To counteract some known problems of GAN training like mode collapse, vanishing gradients etc., 12 (36%) author groups make use of the Wasserstein loss instead of the original loss function based on the Jensen-Shannon divergence or other variants [38,10,47,44,25,21,15,9,46,5,52,45].

A very common approach to improving the systems' performances is to add further additive loss terms. 23 (70%) papers describe this procedure. These additive terms help to train a generator that not only deceives the discriminator but also leads to imputations/forecasts that are close to the real values. Moreover, some additive loss terms help to regularise the training and lead to a better generalisation in the end [28,26,38,35,37,39,10,47,44,40,25,21,15,55,29,9,43,46,57,45,32,11,19].

3.2. Intended use and application domains

For this subsection, we first subdivided the systems into three disjoint clusters corresponding to the extends of the imputation or forecasting horizons. This division is based on the (main) use case presented in the related paper and does not imply that the approach is exclusively used for this purpose. For example, a system that is able to forecast one step can also be used to impute single missing values or even forecast several steps by repeated queries. The subdivision is depicted by the second column in Fig. 2.

Eleven articles [26,49,55,48,29,12,5,57,32,8,11] describe mechanisms for the one-step-ahead forecast, while ten others [28,19,39,47,44,20,9,43,46,56] focus on the prediction of several future steps. The most frequently considered case is the multi-step imputation task, which was examined in 12 publications [38,41,37,35,10,40,25,21,15,7,52,45].

Besides the number of forecasting or imputed steps, the application domains of the approaches can serve as grouping criteria. Several articles describe no special field to which the system is limited by design. However, some projects can be assigned to one or several application domains for which they were created. The grouping according to the application domains is shown in the last column of Fig. 2.

10 methods (30%) come to application in the image/graphics domain, for which the original GAN framework was developed [38,28,19,37,35,39,55,29,9,32].

Another group of five articles (15%) outlines solutions for the imputation/ forecasting of environmental or climatic data [19,47,55,9,52].

Three author groups focus on telecommunication or speech data. Yazdanian et al. and Zou et al. present systems for the prediction of cloud or network utilisation rates, respectively [43,8], while Li et al. aim at improving human speech data [40].

Yin et al. [12] suggest a method for the control of industrial plants, whereas Zhang et al. and Zhou et al. describe systems for the price prediction task [57,11].

Nearly a quarter of all reviewed publications, namely 8, report systems introduced for the biomedical domain [38,26,28,10,44,25,7,32]. Some of these are focused on (tomo)graphic inputs, while other work with non-visual time series. Due to the utilisation of PubMed as a query tool, this group might be overrepresented in our work. However, four of the eight papers were exclusively found with the help of Scopus or Web of Science. Approaches for one-step and multi-step forecasting, as well as imputation, were identified in this area of application. All different methodologies described in Section 3.1 except for one were also found in the group of biomedical papers. To our knowledge, there is no medical system that relies on minimisation during the inference phase.

4. Discussion

Given the success of GANs in various non-medical fields, this review fills a gap by systematically examining current approaches to using GANs to predict or impute medical time series data. The systematic review revealed that there exist several GAN-based methods for the temporal imputation and/or forecasting task. Good results are reported not only from the classic image-based systems but also from methods for univariate or low-dimensional time series. Around 70% of the reviewed publications contain claims about superior performances of the described approaches compared to classic solutions like autoregressive integrated moving average (ARIMA), deterministic inter- or extrapolations with the help of LSTMs, support vector regression etc. The synthesis showed that GAN-based imputation and forecasting approaches are already applied and tested in many subfields of the biomedical domain. Moreover, no certain group of topologies, inputs, outputs and losses has proven to be universally applicable and superior in the medical field. Due to the diversity of this area, the best suiting method cannot be determined without considering the actual use case. The reviewed methods that were not presented in the context of a special field of application and the approaches for computer vision tasks might as well be useful for certain medical imputation/forecasting problems.

Although we could not identify any peculiarities of the GAN-based systems introduced for the medical domain, we found out that especially additive loss terms, as well as conditional GANs, play an important role in the development of GAN-based systems for the forecasting and imputation task in general. Recurrent layers used for en-/decoding the conditioning longitudinal context information (historic, future, exogenous) inside the generators proved themselves useful in several experiments. An interesting finding is that many authors describe deterministic generators that do not have any noise input. This procedure is opposed to the original idea of GAN training presented by Goodfellow et al. [1] but still leads to well-functioning systems.

4.1. Limitations

A question that was not fully answered in the presented publications is the following: "Do GAN-based approaches generally outperform systems that only use an individual neural network (like sequence-to-sequence networks or autoencoders) and that are not trained in an adversarial fashion?". Some publications do not include any such comparison, while others show rather mixed results (like [49,11]). In some situations, the single deterministic versions seem to be superior, whereas other situations or network topologies seem to require the generative adversarial approach. Moreover, similar to Rizvi et al. [34] we would like to see some more work on standardised evaluation criteria for the performance of GANs in general and in the temporal domain in particular. Due to the various qualities and scopes of the data sets as well as the diverse metrics, a quantitative comparison of the performances was not possible.

Another limitation of the review is the selection bias introduced by the restriction to the three databases PubMed, Web of Science and Scopus.

5. Conclusion

In conclusion, it can be stated that the GAN framework - especially the conditional version - is a promising tool for the field of (biomedical) temporal forecasting and imputation due to its generic handling of context information and its flexibility to incorporate all kinds of network building blocks.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Tabular summary

Table A.2

Table A.2
Summary of the analysed publications: References, topologies/methods, deterministic generators, data sources, training set sizes, test set sizes, evaluation metrics, corresponding web repositories. Abbreviations: MRI = magnetic resonance imaging, EEG = electroencephalography, EHR = electronic health record, CV = cross validation, STNR = signal-to-noise ratio, SSNR = segmental signal-to-noise ratio, SSIM = structural similarity index, AUC = Area under the curve, (NR) MS(R) E = (normalised root) mean squared (relative) error, MA(P) E = mean absolute (percentage) error, KL = Kullback-Leibler, PESQ = Perceptual Evaluation of Speech Quality

	Methods	Det.	Data sources	Size Train	Size Test	Metrics	Web
[38]	(de-) convolution, en-/decoder	yes	dynamic contrast enhanced MRI	4 sets (33,890 slices)	8 sets (44,850 slices)	peak STNR & SSIM	–
[26]	GRU, en-/decoder	yes	EHRs of heart feailure patients	2102 patients	same (CV)	AUC, MSE	yes[4]
[28]	(de-) convolution, en-/decoder	yes	MRI of low/high grade glioma patients (L/HGG)	9 LGG + 9 HGG patients	same (CV)	Dice coefficient, Jaccard Index, rel. volume difference, RMSE, sensitivity, specificity	–
[19]	(de-) convolution	no	microscopic images of barley leaves	7000 patches	180 patches	qualitative	–
[41]	(de-) convolution	no	sine waves, cosine waves, Tennessee Eastman Process data, Point machine dataset	8400, 8400, 3200, 9000 (samples)	2800, 2800, 800, 1000 (samples)	RMSE	-
[35]	(de-) convolution	yes	3D time-varying graphics	–	–	peak STNR, SSIM, isosurface similarity, mean opinion score	–
[37]	convolution, LSTM, residual blocks, en-/decoder	yes	3D time-varying graphics	-	-	peak STNR, SSIM, isosurface similarity	–
[39]	(de-) convolution, en-/decoder	yes	3D time-varying graphics	–	–	peak STNR, SSIM, isosurface similarity	–
[10]	GRU, en-/decoder, mixture density	no	100 series of Modular Aero-Propulsion System Simulation	80%	10%	MSE, MAE	–
[47]	(de-) convolution	no	56 NREL Wind and Solar Integration Datasets	80%	20%	temporal and spatial correlation	–
[44]	LSTM, convolution	no	mean daily medication expenditure (Truven Market Scan)	1,306 days	259 days	RMSE	–
[20]	–	no	Ethylene-Methane, Currency, Traffic Flow, IBM stock	8000 samples, 8 years, 8 months, 15 years	3000 samples, 7 years, 12 months, 35 years	MSE	–
[49]	GRU, LSTM, en-/decoder	no	Lorenz equation, Mackey-Glass set, Internet traffic	50%	40%	RMSE, MAE, MAPE, KL divergence	–
[40]	LSTM	no	noisy speech utterances	11,574 utterances	824 utterances	composite signal distortion, composite background intrusiveness, composite mean opinion score, PESQ, SSNR, log-spectral distortion, extended short-time objective intelligibility	yes[5]
[25]	(de-) convolution, residual blocks, en-/decoder	yes	3 EEG datasets	13, 6, 7 (subjects)	1, 1, 1 (subject)	temporal, spatial, frequency and temporal-spatial MSE	–
[21]	GRU for Imputation (GRUI)	no	Physionet Challenge 2012, KDD CUP 2018 Dataset	–	–	indirect, MSE	–

(*continued on next page*)

Table A.2 (*continued*)

	Methods	Det.	Data sources	Size Train	Size Test	Metrics	Web
[15]	GRUI, en-/decoder	no	PhysioNet Challenge 2012 dataset, KDD CUP 2018 Dataset	80%	10%	indirect, MSE	–
[55]	–	yes	typhoon satellite images + velocity fields + typhoon center marking	66 typhoons	10 typhoons	(relative) distance between real and predicted centre	–
[7]	LSTM	–	–	–	–	–	–
[48]	LSTM, graph convolution	no	Store Item Demand, Web Traffic, NOAA China	–	–	MAE, RMSE	–
[29]	(de-) convolution, en-/decoder	yes	MORPH aging database, Cross-Age Celebrity Dataset, FG-NET	8 experiments with different divisions	see left	MAE, automatic face verification, human subjective evaluation	–
[9]	(de-) convolution, en-/decoder	yes	Brassica rapa plant leaf images, Arabidopsis thaliana root images	80%	20%	peak STNR, SSIM, mean Intersection-Over-Union	–
[43]	LSTM, convolution	yes	HTTP requests to 3 different servers	80%	20%	RMSRE, MAPE, median APE	–
[12]	reinforcement, restricted Boltzmann machines	no	3 sets of load series in microgrids	–	–	average frequency deviations, domain specific costs	–
[46]	LSTM, en-/decoder, convolution	yes	sines, stock prices, energy, lung cancer	–	-	posthoc classification error, MAE	yes[6]
[5]	graph convolution	no	road map and traffic speed in Gangnam (Seoul)	80%	20%	MAE, percent RMSE	–
[57]	LSTM	yes	data of stock prices	90%–95%	5%–10%	MAE, RMSE, MAPE	–
[52]	GRUI	no	GEFCom 2014 solar track	–	–	MSE	yes[7]
[45]	GRUI, en-/decoder	yes	Physionet Challenge 2012, KDD CUP 2018, Air quality in Northern Taiwan	–	–	indirect, MSE	–
[32]	(de-) convolution, en-/decoder	yes	T1-weighted MRI of brains	210 patients	same (CV)	SSIM, RMSE	–
[8]	echo state network	yes	3 network traffic sets	66%	33%	NRMSE	–
[56]	LSTM	yes	Kaggle web traffic competition	500 steps	50 steps	RMSE	–
[11]	LSTM, convolution	yes	prices of 42 stocks	59047 min	same (CV)	RMSRE	–

[4] https://github.com/ZJU-BMI/DAL-EP
[5] https://github.com/IMLHF/ulaw-SGAN-for-SE
[6] https://bitbucket.org/mvdschaar/mlforhealthlabpub/src/master/alg/timegan/
[7] https://github.com/stephenzwj/SolarGAN

Appendix B. Textual summary

The work by Cha et al. [38] is focused on improving the temporal (and spatial) resolution of temporal magnetic resonance imaging (MRI). However, the increase of temporal resolution is not reached by generating new frames but by using a GAN-based system that can produce individual high-quality frames by utilising fewer subsequent k-space views than conventional MRI methods. Thus, this method cannot be used as a general imputation approach.

Chu and colleagues [26] solved a medical prediction task and utilised a conditional GAN (cGAN) to improve their prediction basis. Unfortunately, the paper does not reveal any results regarding the performance of this intermediate GAN used for the one-step-ahead forecasting. Nevertheless, the authors describe an increase in the overall prediction performance due to the GAN.

The next publication describes an existing cGAN-based imputation method assessed on large medical data sets. However, the experiments conducted by Dong et al. focus on the imputation of missing values in small vectors of independent variables without any temporal connections [27]. Their results showed that the so-called GAIN approach presented by Yoon et al. [59] outperforms some other state-of-the-art imputation approaches with respect to the above-mentioned task.

Elazab et al. proposed a method for two-step-ahead predictions of 3D MR images including brain tumours [28]. They use one full cGAN for every prediction step and these GANs are each conditioned on the output of the preceding generator (or the initial ground truth image) in combination with precomputed segmentation maps showing tumour regions, white-matter, grey-matter, and cerebrospinal fluid. Thus, this model does not exclusively rely on an autoregressive approach but also includes extrinsic information in every step. The temporality of the suggested system is reached by stacking several jointly trained GANs.

The work by Farajiparvar is motivated by the time delay problem in the domain of telerobotic that is caused by the limited transfer rate between remote robots and corresponding control units [13]. The authors extensively summarised available methods regarding time series prediction. Although they do not present any new GAN approach, their work revealed one more relevant paper on GAN-based time series prediction.

Förster and colleagues present a method to forecast the spread of crop disease symptoms [19]. For this task, they use a cycle-consistent GAN (cycleGAN) whose forward generator is trained to transform a hyperspectral input image showing a section of a plant leaf into a hyperspectral image showing the same section but one day later. By repeatedly applying the trained forward GAN the authors generate seven-step-ahead forecasts on healthy and diseased plants. Unfortunately, their work only includes a qualitative evaluation that is hard to understand without any agricultural or botanical knowledge. Due to the utilised cycleGAN, the approach is only applicable to forecasting tasks regarding images or other high dimensional time step values.

The publication by Guo et al. not only introduces a new GAN for multivariate time series imputation (MTS-GAN) but also summarises many existing imputation approaches [41]. The MTS-GAN is based on a plain convolutional GAN for image synthesis tailored towards multivariate time series. After the MTS-GAN is trained to synthesise time series, only its generator is used for the imputation task. To this end, the noise vector has to be found that produces the closest resemblance of the incomplete input series when used as an input to the generator. Since the generator always produces complete series, the values of the synthesised series that corresponds to the minimising noise vector can be interpreted as imputation values. In their experiments, Gio et al. showed that their approach outperforms denoising autoencoders as well as classic interpolation-based methods on several artificial and real-world data sets.

The following two papers are by the author duo Han and Wang. The first work focuses on the increase of the temporal resolution of volume time series [37], while the second aims at enhancing the spatial resolution of these data [35]. Especially, the first work is relevant for the present review. Therein, the authors presented a conditional GAN that is trained to compute missing 3D volumetric samples of a time series when given the closest existing past and the closest existing future sample. Due to the volumetric input and output data, the generator uses convolutional Long Short-Term Memory (LSTM) networks. However, in contrast to the approach by Cha et al. [38], the overall system can be adapted in order to handle 2D and 1D data. Han and Wang showed in several experiments that their approach outperforms other imputation methods with respect to the visual quality of the results.

In the most recent work that was published in cooperation with the two aforementioned authors, the researchers describe a GAN-based mechanism to reconstruct a bivariate time series based on the univariate series of one included variable [39]. Again, the focus lies on the prediction of 3D volumetric time series but the general idea can be used for 2D and 1D data as well.

Huang et al. motivate their research on imputation with the aim of improving medical prognostics and health management [10]. They present a cGAN based on a recurrent variational autoencoder (RVAE) to not only interpolate missing values of multivariate time series but also to predict a binary End-of-Life (EoL) state at every time step. The generator consisting of an RVAE is trained to produce hyperparameters of a mixture of Gaussians in every step, which in turn is used to draw a possible imputation value. Moreover, in every step the autoencoder outputs a 2D one-hot vector predicting whether EoL is reached or not. To handle incomplete time series with an RVAE, Huang et al. utilise the modified Gated Recurrent Unit (GRU) introduced by Luo et al. [21] (see below). Similar to the training methods presented by Han and Wang, several error terms were added to the generator loss to enforce the similarity of the predicted and real features or EoL values. The experiments proved that their approach outperforms several classic imputation methods. However, for small missing rates, the framework presented by Luo et al. [21] showed better performances.

The approach by Jiang et al. [47] is similar to the one presented by Guo et al. [41]. The authors suggest to pretrain a Wasserstein GAN (WGAN) on the time series synthesis task (without any prediction). Afterwards, this GAN should be used to find several noise variables that lead to close resemblances of a precomputed forecast series when fed into the generator. The precomputation of the forecast which is only refined by the described approach is not explained. By outputting several possible forecasts the authors want to represent uncertainty.

Kaushik et al. also base their approach for the prediction problem on a synthesis task [44]. They train several GANs with different topologies and error combinations to synthesise individual time steps describing the daily average drug expenditures of patients. Afterwards, the trained generators are queried several times to produce forecast steps (one at a time). The generator is neither conditioned on real past values nor on its own past results when synthesising future time steps. Thus, the approach is only useful for stationary time series. The authors showed in several experiments that the addition of a second loss component, which penalises differences between predicted and real step values, to the plain generator loss leads to better performances. This is in line with the findings presented in [21,35,39].

Koesdwiady et al. present a cGAN that is trained to synthesise one past time step value when given some noise input and the current time step value [20]. However, this cGAN is only used to produce augmented training data in the described experiments. Still, it leads to improvements when used in combination with a simple multilayer perceptron that is trained for the 8-steps ahead prediction.

The *ForGAN* presented by Koochali et al. can predict a single step ahead conditioned on a series of historic (and present) values [49]. Both, the generator and the discriminator use a single RNN and dense layers to compute the forecast or the decision between real and fake, respectively. The authors compare the performance of the generator trained in the usual adversarial setup against the performance of a “plain generator”. The plain version has the same topology as the original one but is trained directly without the help of a discriminator to lower the root mean squared error between prediction and real step. Their experiments show that the second generator outperforms the one trained in the adversarial framework on several data sets. However, the experiments also prove that there is a data set on which adversarial training leads to better performances.

Li et al. developed a cGAN to generate magnitude spectra of enhanced speech signals conditioned on the magnitude spectra of the noisy versions [40]. To some extent, the speech enhancement task can be interpreted as a special case of the imputation task with extrinsic information. In this case, the extrinsic information is the noisy signal and the full time interval of the clear speech is to be filled in. The presented approach is highly specialised towards the speech domain and shows state-of-the-art performances in several experiments.

The underlying idea for the work by Luo et al. [25] is comparable to aims presented by Cha et al. and Han et al.[38,35]. All three teams introduced GAN-based methods for the temporal upsampling task. Luo et al. focus on EEG signals and besides the improvement of the temporal resolution they also consider the enhancement of the individual measurements (sensitivity). For this task, the authors suggest a cGAN that is mainly composed of convolutional residual blocks (generator) and convolutional layers (discriminator). Similar to the generator loss terms presented in [35,39,44], the generator loss in the described project also has an additional part that does not belong to the GAN model. The authors introduce a so-called spatial-temporal-frequency loss to improve the generator’s upsampling performance. In the experiments, several data sets with different sampling rates, numbers of channels and sizes as well as plain and Wasserstein training were used. The results show that the presented approach can improve the EEG reconstruction when trained on a data set that has comparable characteristics (sampling sensitivity and channels). If however, the sampling sensitivity during inference differs from the one used during training, the approach leads to mediocre or even bad results that need further improvement.

The following two papers were produced with the collaboration by the first author Yonghong Luo. Both deal with the multivariate time series imputation with the help of a WGAN. The motivation in both cases was the incapability of existing imputation methods for modelling temporal dependencies. The first work describes the newly developed *gated recurrent unit for data imputation* (GRUI) that incorporates the time lag between two existing values [21]. A classic GRU does not use this information for its computation. Based on this GRUI a plain GAN is trained on the time series synthesis task. Afterwards, the trained generator is used to find imputation values for a given series with missing steps. To this end, a similar approach as described by Guo et al. [41] is used. However, Luo et al. not only consider the similarity between the generated and real series but also the discriminator output during the search for a good noise vector. Both have to be maximised for this task. In their experiments, the authors could show that for some data sets the GRUI-based GAN outperforms GANs that make use of classic GRUs and that their approach is superior to state-of-the-art methods.

The second publication by Luo et al. builds upon their previous one [15]. Instead of using plain GAN without any conditional input, they present a cGAN with Wasserstein loss this time. The generator, which is a GRUI-based AE, gets a time series containing missing values as the conditional input.

Moreover, additive noise is used as the noise input. A squared error is added to the generator loss during training to enforce better imputation performance. This setup allows end-to-end training in contrast to the previous version and also outperforms the older version on most tasks.

The paper by Zhaojie Luo et al. has a strong application-dependent motivation. The authors try to forecast the oil price by a GAN model [22]. On the questionable assumption that deep learning approaches cannot handle univariate time series values, the authors suggest preprocessing such series to transform them into their 2D wavelet coefficient representations of fixed size. The described training algorithm only minimises the GAN loss by updating the generator's and the discriminator's weights. This contradicts the fundamental idea of adversarial learning. Moreover, the experiments reveal that the wavelet transformation leads to worse results than a GAN trained in the usual time domain. Overall, the described approach is unclear and its performance is bad.

Mahmood and Abbasi suggest using an ensemble method of two or more base predictor instances for the time series prediction task [23]. One instance is trained with the normal training data, while all the other instances (same type) are trained with synthetically generated training data. In contrast to the previously described approaches, this framework only uses GANs to synthesise additional training data. Still, the results show that for the prediction of phishing attacks, the integration of synthetic data into the training procedure leads to better performances in most cases.

Niu and colleagues presented a time series anomaly detection approach based on RVAE-cGANs [30]. The underlying idea is to train an LSTM-based RVAE as the generator of a cGAN and make it learn the distribution of only normal time series. After the training, the generator RVAE is thought to be able to reconstruct normal series from their latent representation in a way that the discriminator cannot differentiate the generated time points from the real ones. During the anomaly detection phase, the absolute difference between every generated time step value and its correspondence in the real input series is used as an anomaly score. Moreover, the discriminator decision on all input series is used as an additional anomaly score. Since the discriminator was only trained to identify normal samples as such, it is likely that it identifies anomalous steps of the input as "fake". Although the method was presented for the anomaly detection task, the trained generator might also be useful for the imputation task.

The paper by Pang et al. has again a more pragmatic aim. The authors propose a method to predict electricity consumptions for individual buildings [18]. They focus on the problem of forecasting such measurements for new buildings without many historic data points. In their approach, several cGANs are trained to generate additional synthetic historic data points for a certain building based on the real historic data of comparable buildings. However, the actual prediction is computed by a plain LSTM that makes use of the real and the synthetic historic data. A disadvantage of the method is that it needs several trained GANs for the consumption prediction of a single building.

Panwar et al. present several GAN-based approaches to synthesise EEG signals of fixed size [54]. However, the described prediction task does not refer to the temporal forecasting, but to the binary classification of whether an EEG snippet corresponds to a certain event experienced by the testee. Thus, the results cannot be used directly for the prediction and imputation task.

We found one recent survey paper that summarises current developments of GAN-based approaches regarding different fields of applications [34]. Rizvi et al. identified 23 different application domains, of which *Market prediction and forecasting* and *Weather forecasting* overlap with the domains investigated in our review. The authors found 3 papers corresponding to these two topics, namely [55,14,22] which were also identified by us and one paper by Chen et al. [58] that we did not include in our review during the first phase. Although Rizvi et al. claim that the paper by Chen et al. includes a description of a weather forecasting mechanism, we could only find approaches for the generation of synthetic time series figuring the generation of renewable powers (wind/sun) over time.

In the work by Rüttgers et al., the applicability of cGANs for the prediction of typhoon tracks based on satellite images is evaluated [55]. The presented GAN was trained to produce one-step ahead satellite images of a typhoon based on the input containing several sorted historic images. Their experiments proved that the GAN-based approach is a cost-efficient and accurate alternative to the existing typhoon forecasting methods and that the integration of further extrinsic information (here: wind velocity fields) can lead to improved forecasts.

Sharma and Hamarneh developed and evaluated a cGAN for the imputation of missing MRI channels [31]. The presented generator was trained to fill in one to three missing channels of 4-channel 2D MRIs given the existing one(s). During training, the discriminator does not compute a single decision for a filled-in channel, but outputs individual decisions for all 16×16 patches of every missing channel. The approach outperformed all presented competitors in the conducted experiments.

The work by Song et al. aimed at developing a pipeline for the generation of highly accurate cardiac pulse time series based only on videos of the testees' faces (remote photoplethysmography (rPPG)) [33]. The presented cGAN is the last building block of this pipeline and was trained to denoise and improve pulse signals produced by an existing remote photoplethysmographic algorithm. The rPPG task can be viewed as an imputation task with extrinsic information (cf. speech enhancement task described by Li et al. [40]). However, the presented approach depends on an existing "imputation" algorithm and the included cGAN is specialised for the improvement of existing pulse series and not for the forecasting/imputation task.

Stinis et al. study a sub-problem of the imputation/forecasting challenge, namely the enforcement of certain constraints during the inter- and extrapolation of time series via GANs [16]. More precisely, they describe several adaptations to the plain GAN training that allow to constraint the GAN-based inter- or extrapolations of flow maps of dynamical systems. Their results show that the enforcement of constraints during and/or after training lead to an improvement of efficiency and accuracy. These findings can be interpreted as an extension to the individual results described in [35,39,44,25] that regard the additive (residual) losses added to the plain loss definitions of the original GAN framework.

The project by Tian et al. [14] has a similar objective as the one by Pang et al. [18], to forecast energy consumption. By training a GAN for the time series synthesis and applying the resulting generator to generate additional training series, the authors try to improve existing data-driven forecasting approaches. Their experiments revealed that the supplementary synthetic series lead to better performing (base) predictors like feed-forward NNs when used during training.

Venkatesh et al. present a cGAN for the prediction of precipitation amounts over time in India [50]. During a preprocessing step, they extract and select features of historic rainfall series with the help of Fourier transform, Autoregressive Integrated Moving Average (ARIMA), a pretrained VAE, Principal Component Analysis and others. The resulting feature vectors are used as a conditional input to the LSTM-based generator. Unfortunately, it stays unclear how many time steps are predicted based on the input vector and what data are used. Moreover, the authors claim that the presented method reaches an accuracy of 99%, what disagrees with the visual representations of the predicted series plotted against the real ones.

Wang et al. introduce a framework for the weather classification of a single day based on the corresponding irradiance time series [6]. Moreover, they present a system that builds upon the previously mentioned one and predicts the irradiance time series of the following day. Before the actual training of the classification approach, the authors train one WGAN for every weather class (e.g. "Sunny in the morning, rainy in the afternoon") to synthesise corresponding irradiance series. Afterwards, the WGANs are used to enrich the existing training data for the classification task. The authors comprehensively analyse the effects of different GAN training strategies (pure GAN, WGAN, WGAN with gradient penalty) and the influence of the training set augmentation on the classification task. The irradiance forecasting approach is unspecified. The authors only show that the use of class-based forecasting leads to improved performances. Class-based means that a single forecasting mechanism is trained for each weather class and that during inference the one corresponding to the weather predicted by meteorologists is used.

In the short communication published by Weihan Wang [7], the author briefly describes the usage of a cGAN consisting of a bidirectional LSTM (generator) and another unspecified RNN (discriminator) for the imputation task in medical time series data. Due to the brevity of the paper, the conducted experiments stay unknown to the reader, but Wang claims that his approach outperforms several classic methods and reaches an accuracy of over 95% even on multivariate time series with a missing rate of around 80%.

Wu et al. focus on the one-step-ahead multivariate time series prediction and particularly on the integration of inter-series dependencies with the help of a cGAN [48]. A Peculiarity of their suggested framework is the division of the generator into two parts and the graph-based dependency representation between series. The first part of the generator computes an interaction matrix based on a noise input. The individual entries of this matrix represent interdependencies between two series and are used by the second part of the generator as an additional input to the historic time series data. The discriminator has to discriminate between real and fake one-step-ahead predictions when given the actual historic values as context. In several experiments on real-world data the authors could show the superiority of their model over classic methods like ARIMA or single RNNs.

Yang et al. describe a cGAN for the image generation of aged faces conditioned on images of the younger faces and the target age ranges [29]. Besides a convolutional generator and several discriminators (one for each target age range), additional paths are added to the discriminator framework in order to enforce small pixel-level loss and identity preservation. The overall approach is highly specialised for the visual age progression task. It leads to more photorealistic and accurate results than some other state-of-the-art approaches.

In their paper Yasrab et al. describe an approach for the several-steps-ahead prediction of image segmentation masks regarding growing plants [9]. The utilised conditional WGAN is conditioned on six historic binary or n-classes 2D segmentation masks and trained to predict several future segmentation masks that correctly represent the growth of the corresponding leaves or roots. The extending topology (additional layers) of the generator and discriminator during training is a special feature that was adopted from the FutureGAN training introduced by Aigner and Körner [60].

The work by Yazdanian and Sharifian is motivated by the need for accurate multistep-ahead cloud workload predictions [43]. The suggested approach consists of a preprocessing step for every input series of historic values and several GANs as well as LSTM networks. During preprocessing the size of the input (context) window is determined by searching for the smallest lag that has a partial autocorrelation of 0. This value is then used as the window size. Moreover, the cropped input is subdivided into several series (intrinsic mode functions (IMF)) by an empirical mode composition. The sum of all IMFs represents the actual input. Afterwards, every high-frequency IMF is handed to a cGAN (generator: LSTM, discriminator: CNN) specialised for this particular frequency (range) that produces an IMF that contains one or several additional time steps. For low-frequency IMFs the authors train only LSTMs for the same prediction task. In the end, all proceeded IMFs are summed up to get the actual time series predictions. On some datasets, this framework outperforms purely LSTM- or CNN-based predictors, while on others it lags behind.

Yin and Zhang present a method for the management of smart micrografts that contain several sources of renewable energies [12]. For this approach, a GAN is trained within a reinforcement framework to output future actions that control the energy sources. At least for readers like us who are unfamiliar with the functionality of microgrids, the description of the algorithms and experiments stay unclear at some points. Thus, we refrain from further elaborations.

Yin et al. combine an LSTM-based AE (generator) and a temporal CNN (discriminator) into a cGAN that can forecast several steps of a univariate time series when given past values of this and several exogenous series [46]. The generator's encoder transforms the extrinsic multivariate series into a latent series of fixed dimensionality while using two attention mechanisms. The corresponding decoder, which uses temporal convolution and attention as well, gets the latent context series in combination with the past values of the target series and computes several predictions for this target. The discriminator consists of stacked temporal convolutions. On several real-world data sets, this new approach could outperform other NN-based forecasting mechanisms. However, for some data sets a Seq2Seq RNN with attention was the better choice.

The approach by Yoon et al. was tailored towards capturing temporal correlations in time series [24]. The system is trained to produce synthetic time series (and additional static information), which in turn can be used to enrich training sets for the prediction task. The authors combine two training objectives. The first one is the minimisation of the distance between real and generated joint distributions of all time steps in a series. The second aim concerns the minimisation of the deviations between the real and the fake conditional distributions of the next time step given the previous step. To this end, an AE and a GAN are combined by training the generator to synthesise latent series which lie in the latent space of the AE. Not only the usual GAN loss and the AE's reconstruction loss are combined, but also a loss measuring the distance between the generated next step in the latent series and the original AE output is added. After training, the generator in combination with the AE's decoder is used for the actual synthesis.

The work by Yu et al. focuses on the development and evaluation of a system for the prediction of traffic speeds in individual road segments [5]. The key component of the suggested framework is an extended Graph CNN that is adapted to handle temporal changes. This setup is also augmented by a simple feedforward discriminator and jointly trained with the Wasserstein approach. In an experiment on real-world data, the adversarial approach could not increase the predictive performance when compared against the plain extended Graph CNN.

Zhai and Zhou apply deep learning to the temperature prediction of heating furnaces [36]. The centrepiece of their framework is a temporal CNN that is used in combination with transfer learning. This temporal CNN is trained to predict one-step-ahead temperatures based on historic values of independent variables. By using transfer learning, information about temperature dynamics learned for a certain spatial area inside the furnace can be reused for other zones. In addition to classic transfer learning that is done by retraining only the higher layers, the authors try to improve this method by adding a GAN. The generator is trained to adapt values of independent variables from the target zone to values that are more similar to ones of the source domain. Afterwards, the generator is applied to change all target training data before the transfer learning is conducted. Their experiments revealed that this procedure leads to better results than plain transfer learning.

Zhang's and Guo's works [4,3] are comparable to the one by Pang et al. [18] as both groups focus on the forecasting of electricity consumption. In their first work regarding this topic, the authors use several time series of context variables like meteorological factors, electricity prices etc. as inputs [3]. All series undergo a multistage preprocessing that contains a decomposition, a dimensionality reduction and an encoding into images. Afterwards, the now visually encoded inputs are processed by an ensemble of cooperatively trained convolutional cGANs to produce forecasts that are combined with a Huffman coding. The authors claim that they have used the combined outputs of the discriminators as a forecast. Unfortunately, it stays unclear if this is only an error in the description or if they used a special discriminator. Their experiments showed that the new method outperforms several other neural network-based prediction approaches like plain LSTMs and CNNs.

The second paper by Zhang and Gou was published only two months after the first one and involves the same problem [4]. Moreover, the same general structure is used for the second forecasting framework. Again a preprocessing is conducted on the input series. This time a Kalman filter and a temporal weighting are used. Afterwards, an ensemble of three coupled GANs is trained to predict the energy consumption based on the preprocessed inputs. Also in this publication, it is described that the outputs of the discriminators are combined for the final prediction. It still stays unclear how the decisions by the discriminator can serve as predictions.

Kang Zhang and colleagues introduce a cGAN for the prediction of closing prices of stocks based on historic values and additional extrinsic factors [57].The generator consists of an LSTM, while the discriminator is a multilayer perceptron. The generator has no noise input and minimises not only the normal generator loss but also the mean squared error between predicted and real closing price during training. On a data set containing historic data of a single stock, their approach outperformed an LSTM and the support vector regression method.

Wenjie Zhang et al. propose a method for the imputation of multivariate time series representing solar data[52]. To this end, a conditional WGAN is trained which utilises GRUIs inside the generator and discriminator. This system extends the framework presented in [21] by conditioning the generator on real missing series. For inference, a noise input is searched that not only minimises the difference between real non-missing values and their synthesised counterparts, but also maximises the discriminator's decision on all synthesised values. On a single solar data set, the new approach outperformed several existing methods including other GAN-based imputation frameworks.

The work by Ying Zhang et al. [45] directly builds upon the projects by Luo et al. [21,25] and aims at improving these. The general topology of the new Wasserstein cGAN is similar to the previous one presented in [25]. A GRUI-based AE serves as the generator and a GRUI followed by a feedforward layer serves as the discriminator. This time, however, the authors do not use any noise input but let the generator's encoder compute a fixed context vector based on the input data with missing steps. This context is handed to the decoder in addition to the input data and the missing values are predicted while making use of the real data (if available) or the previously predicted ones (if not). Their new approach outperformed the older ones on real-world medical and air quality data sets. However, due to the omission of noisy inputs, the new generator is deterministic.

Yan Zhao et al. pursue a similar goal as Elazab et al.[28] during their project described in [32]. They want to predict a 3D brain MRI based on historic versions and additionally predict the stage of the Alzheimer's disease progression. In addition to a forecasting cGAN conditioned on a historic 3D image and extrinsic information (age, gender etc.), they train a classifier that learns to classify the disease status based on synthesised brain images. The GAN loss is extended by L2 and gradient difference losses in the image and the frequency domain to better direct the generator training. The experiments showed that the conditioning on extrinsic information leads to better 3D predictions as well as to improved disease status classifications.

Bin Zhou and colleagues describe a system for the short-term prediction of wind power [51]. They claim to use an alternative GAN framework. However, the presented network is neither trained in an adversarial fashion nor is the "discriminator" used for discrimination but for the actual forecasting. Thus, we exclude this work from our review.

The paper by Jian Zhou et al. deals with a new approach for the network traffic prediction that makes use of a special version of an echo state network (ESN) integrated into the cGAN framework [8]. In contrast to the classic version, the newly presented ESN has an adaptive reservoir and serves as a generator. The corresponding discriminator consists of a 3-layer feedforward net. A vector summarising a window of historic traffic data serves as the conditioning input to the ESN generator that outputs a one-step-ahead prediction. The error is used to update the reservoir weights of the ESN, which makes it adaptive. On several real data sets, the new GAN-based adaptive ESR outperforms its static counterpart as well as pure LSTMs and deep belief networks.

Kun Zhou et al. compare three existing methods for the time series forecasting, LSTMs, temporal CNNs and GANs [56]. Moreover, they experiment with additional attention mechanisms added to the LSTM or the temporal CNN and an AE that consists of two LSTMs. Their proposed GAN that uses a simple feedforward network as a generator does not lead to better performances than ARIMA. However, they could empirically show that attention mechanisms cause better performances when added to a time series predicting LSTM.

The following publication by Kun Zhou again combines some analyses on existing forecasting approaches and the presentation of a GAN model [42]. This time, the authors suggest an LSTM as the generator for the GAN that is trained with the help of the Wasserstein loss. Unfortunately, no quantitative results are presented. Thus, a reproduction of the experiments seems impossible.

Similar to Zhang et al. [57], Xingyu Zhou and colleagues introduce a cGAN-based method for the one-step-ahead stock price prediction [11]. They combine an LSTM working on past series of extrinsic information like trading volume, turnovers etc. with a CNN that is trained to discriminate between synthetic predictions by the LSTM and real ones. The GAN generator loss is extended by forecasting losses. In experiments on real stock price series, the authors could prove that their approach outperforms static methods like ARIMA and simple NN-based systems. Although the GAN performs best in most setups, there are certain constellations in which adversarial training leads to worse results than the exclusive LSTM training.

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