1.Liquid neural networks

<https://ojs.aaai.org/index.php/AAAI/article/view/16936>

2.Linear and nonlinear modeling approaches for urban air quality prediction

[Linear and nonlinear modeling approaches for urban air quality prediction - ScienceDirect](https://www.sciencedirect.com/science/article/abs/pii/S0048969712004809)

3. Forecasting air quality index using regression models: A case study on Delhi and Houston

[Forecasting air quality index using regression models: A case study on Delhi and Houston | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/abstract/document/8300926)

4. Forecasting of air quality in Delhi using principal component regression technique

[Forecasting of air quality in Delhi using principal component regression technique - ScienceDirect](https://www.sciencedirect.com/science/article/pii/S1309104215304700)

5. Forecasting air quality time series using deep learning

[Full article: Forecasting air quality time series using deep learning (tandfonline.com)](https://www.tandfonline.com/doi/full/10.1080/10962247.2018.1459956)

6. Forecasting of daily air quality index in Delhi

[Forecasting of daily air quality index in Delhi - ScienceDirect](https://www.sciencedirect.com/science/article/abs/pii/S0048969711009661)

7. Deep learning architecture for air quality predictions

[Deep learning architecture for air quality predictions | Environmental Science and Pollution Research (springer.com)](https://link.springer.com/article/10.1007/s11356-016-7812-9)

8. Air Quality Index prediction using an effective hybrid deep learning model

[Air Quality Index prediction using an effective hybrid deep learning model - ScienceDirect](https://www.sciencedirect.com/science/article/abs/pii/S0269749122016189)

9. Air Quality Prediction: Big Data and Machine Learning Approaches

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10. Machine Learning-Based Prediction of Air Quality

[Applied Sciences | Free Full-Text | Machine Learning-Based Prediction of Air Quality (mdpi.com)](https://www.mdpi.com/2076-3417/10/24/9151)

11. Time Series Analysis and Forecasting of Air Quality in India

[Time Series Analysis and Forecasting of Air Quality in India | IEEE Conference Publication | IEEE Xplore](https://ieeexplore.ieee.org/abstract/document/10179673)

12. Forecast Energy Consumption Time-Series Dataset using Multistep LSTM Models

<https://iopscience.iop.org/article/10.1088/1742-6596/1933/1/012054/meta>

2.Linear and nonlinear modelling approaches for urban air quality prediction

Intro-

* Air quality affects ecology, environment, and public health.
* Linear and nonlinear modelling used to predict urban air quality.
* Respirable suspended particulate matter (RSPM) and pollutants like SO2 and NO2 considered.
* Artificial neural networks (ANNs) performed better than linear models.
* GRNN model yielded high correlation for RSPM, NO2, and SO2.
* Method  
  Linear modelling: Partial least squares regression (PLSR)
* Nonlinear modelling: Multivariate polynomial regression (MPR), artificial neural network (ANN)
* ANN models: Multilayer perceptron network (MLPN), radial-basis function network (RBFN), generalized regression neural network (GRNN)
* Results
* Linear and nonlinear modelling approaches were used to predict urban air quality.
* Nonlinear models (MPR, ANNs) performed better than linear PLSR models.
* ANN models (MLPN, RBFN, GRNN) had comparable performance, with GRNN outperforming the others.
* Optimal GRNN models yielded high correlation for RSPM, NO2, and SO2.
* Sensitivity analysis showed SO2 as the most influencing parameter in RSPM model.
* Conclusions
* Nonlinear models (MPR, ANNs) performed better than linear PLSR models.
* ANN models (MLPN, RBFN, GRNN) showed excellent predictive and generalization capabilities.
* GRNN models performed better than MLPN and RBFN models.
* SO2 was the most influencing parameter in RSPM model.
* SPM was the most important input variable in NO2 and SO2 models.

3. Forecasting air quality index using regression models: A case study on Delhi and Houston

* Intro
* Paper focuses on monitoring air quality using regression models.
* Support vector regression (SVR) and linear models were implemented.
* AQI is dependent on pollutant concentrations of NO2, CO, O3, PM2.5, PM10, and SO2.
* SVR exhibited high performance in terms of quality measures.
* Methods used
* Support vector regression (SVR)
* Multiple linear regression with gradient descent, stochastic gradient descent, mini-batch gradient descent
* Results
* Different regression models were used to forecast air quality index (AQI).
* Support vector regression (SVR) exhibited high performance in terms of quality measures.
* Statistical criteria such as MAE, MAPE, R, RMSE, and IA were used to evaluate the models.

4. Forecasting of air quality in Delhi using principal component regression technique

* Intro
* Increasing interest in air quality due to health effects
* Need for accurate forecasting models of Air Quality Index (AQI)
* Statistical models used to predict pollutant concentrations
* Principal component regression (PCR) technique used for forecasting AQI
* Study conducted for four different seasons and compared statistical error analysis
* Literature Survey
* Increasing public interest in air quality and health effects of pollution.
* Short-term air pollution forecasts provided by local authorities.
* Air Quality Index (AQI) used for air quality management.
* Study aims to forecast short-term daily AQI using previous day's AQI and meteorological variables.
* Study conducted for four different seasons.
* AQI estimated for seven years at ITO for criteria pollutants.
* Principal component regression (PCR) technique used for AQI prediction.
* PCR model performed better in winter compared to other seasons.
* Statistical error analysis showed lower normalized mean square error (NMSE) in winter.
* Other statistical parameters supported the same result.
* Methods Used
* Formation of sub-indices of each pollutant
* Aggregation of sub-indices using breakpoint concentrations
* Principal component regression (PCR) technique for short-term AQI forecasting
* Computation of principal components using covariance of input data matrix
* Validation of PCR model using independent data from 2006
* Analysis of model accuracy through statistical parameters
* Results
* MLR model performs satisfactorily in all seasons, better in winter.
* PCR model performs better than MLR model, especially in winter.
* Forecasted AQI values can be explained by selected input variables.
* Overall performance of PCR model is better compared to MLR model.
* Previous day's AQI is a common variable for all seasons.
* Conclusions
* MLR and PCR models were used to forecast daily AQI at ITO.
* PCR model performed better in winter compared to other seasons.
* Use of principal components reduced collinearity problems in MLR.
* PCR model was found to be better than MLR in 2006 validation period.
* Air quality forecasting is helpful for authorities and public health protection.

5. Forecasting air quality time series using deep learning

* Intro
  + Tropospheric ozone (O3) is a secondary pollutant that impacts human health.
  + Over 21,000 premature deaths in Europe are attributed annually to O3 exposure.
  + This paper trains a deep learning model to predict O3 concentrations.
  + The model uses a recurrent neural network (RNN) with long short term memory (LSTM).
  + RNNs are well-suited for air concentration prediction due to their ability to incorporate sequential history.
  + Tropospheric O3 was chosen as a parameter to forecast due to its complex formation processes and sources.
* Literature Survey
  + Majority of tropospheric O3 is generated through anthropogenic sources.
  + Various factors impact tropospheric O3 formation, including nitrogen oxides, VOCs, chlorine, solar radiation, relative humidity, and ambient temperature.
  + Local concentrations of O3 are influenced by weather patterns and terrain.
  + O3 reacts with NO2 to form NO3, which further reacts to form nitric acid.
  + Additional contributions to O3 concentrations come from stratosphere-troposphere exchange.
  + Modeling O3 is complex due to multiple chemical and transport phenomena.
  + Supervised machine learning techniques, such as ANNs and SVMs, have been used to predict O3 concentrations.
  + ANNs provide better predictive results than linear models and time series modeling.
  + Dimensionality reduction techniques, such as PCA, are used to remove irrelevant inputs.
  + FFNN architecture is commonly used for air quality forecasting.
  + Recent studies highlight the limitations of FFNNs and the tendency to over-fit training data.
  + Previous air quality forecast studies were based on continuous concentration values.
* Methods Used
  + Decision trees were used for binary classification and prediction.
  + MinMaxScaler function was used for scaling individual observations.
* Results
  + The network trained well with all 25 input features.
  + MAE for this scenario is 0.41 ppb during training and 0.37 ppb during testing.
  + Residuals show a normal distribution tendency with a positive bias.
  + Many features were removed without impacting network performance.
  + Overall training error improves with fewer input features.
  + The 5 feature data set was used for evaluation.
  + Parameter sensitivity analysis was performed on a model with default values.
  + RNN has an order of magnitude improvement over FFNN or SVM models.
* Conclusions
* MLR and PCR models were used to forecast daily AQI at ITO.
* PCR model performed better in winter compared to other seasons.
* Use of principal components reduced collinearity problems in MLR.
* PCR model was found to be better than MLR in 2006 validation period.
* Air quality forecasting is helpful for authorities and public health protection.
* Conclusions
* Advanced Deep Learning techniques were used to predict air quality time series.
* The methodology produced good results using the validation data set.
* The LSTM model provided very good results for this case.
* The RNN performed significantly better than other common forecasting models.
* LSTMs can be applied to other environmental time series challenges.

6.Forecasting of daily air quality index in Delhi

* Intro
  + Air pollution is a growing concern globally.
  + Air pollutants can have severe health effects.
  + Monitoring and forecasting of air pollutants is advised.
  + Statistical models are used for forecasting pollutant concentrations.
  + Air Quality Index (AQI) is used to report daily air quality.
  + This study aims to develop forecasting models for daily AQI.
  + Models include time series ARIMA, principal component regression, and a combination.
  + Performance of models evaluated using observed pollutant concentrations.
  + Model 3 shows the best agreement with observed values.
  + Meteorological parameters are assessed using principal component analysis.
  + Variation of AQI is found to be negligible between weekends and weekdays.
* Methods Used
  + Estimation of AQI through USEPA method using daily observed concentration of air pollutants
  + Three statistical models used for forecasting daily AQI: ARIMA, PCR, and combination of both
  + Evaluation of forecasted values by comparing them with observed concentrations of air pollutants
  + Use of daily air quality data of RSPM, SO2, NO2, and SPM from 2000-2006 at ITO, Delhi
  + Training of models using AQI and daily averaged meteorological variables as input parameters
* Results
  + The daily AQI was estimated using monitored concentrations of criteria pollutants in all four seasons.
  + The percentage of very poor and severe descriptors of AQI varied across seasons.
  + Model 3 showed better agreement with observed values compared to models 1 and 2.
  + Meteorological parameters such as rainfall and temperature were significant in predicting AQI.
  + Variation of AQI between weekends and weekdays was found to be negligible.
* Conclusions
* All seven days of the week have similar air pollutant concentrations.
* Model 3 (combination of ARIMA and PCR) performs satisfactorily for air quality forecasting.
* Uncertainties exist in the model due to input data quality.
* Combining statistical models with deterministic models can improve results.
* Model 3 can be used for daily air quality forecasting in urban cities.
* Results can be used for decision making and precautionary measures.

7.Deep learning architecture for air quality predictions

* Intro
  + Air pollution is a global concern affecting human health and sustainable development.
  + Current air quality prediction methods using shallow models are unsatisfactory.
  + This paper proposes a deep learning-based method for air quality predictions.
  + The method considers spatial and temporal correlations using a stacked autoencoder model.
  + The proposed method outperforms traditional time series prediction models.
* Methods Used
  + Stacked autoencoder model is used for air quality predictions.
  + Greedy layer-wise training is used for the stacked autoencoder model.
  + Spatial and temporal correlations are considered in the model.
  + Traditional squared error loss function is used.
  + BP algorithm with gradient-based optimization technique is used for training.
* Results
* The STDL model showed different predictive performances for different stations.
* The model captured 98.24% of the explained variance between recorded and predicted PM2.5 concentrations.
* The Zhiwuyuan station had the highest relative error and a higher MAPE value.
* The model presented consistent performance in each season.
* The prediction rank rate of the model was high for each air quality rank.
* The STDL model had more accurate predictions than the STANN, SVR, and ARMA models.
* The STDL model had lower RMSE, MAE, and MAPE values compared to other models.
* The deep architecture method with unsupervised pre-training improved prediction performance.
* Conclusions
  + Developed a spatiotemporal deep learning-based model for air quality prediction.
  + Model extracts latent air quality feature representations, especially nonlinear spatial and temporal correlations.
  + Model can predict air quality of all monitoring stations simultaneously.
  + Model shows satisfactory seasonal stability.
  + Model outperforms STANN, ARMA, and SVR models in air quality predictions.
* Limitations
* Deep networks trained with the BP algorithm have poor performance.
* Traditional time series prediction models produce unsatisfactory results.

8. Air Quality Index prediction using an effective hybrid deep learning model

* Intro
  + Paper focuses on air quality evaluation and prediction using big data and machine learning.
  + Reviews research on air quality evaluation standards, big data analytics, and machine learning models.
  + Highlights future research needs and directions in air quality evaluation.
* Literature Survey
  + Reviews and compares current research work on air quality evaluation.
  + Focuses on big data analytics and machine learning models and techniques.
  + Highlights observations on future research issues, challenges, and needs.
* Methods Used
  + Big data analytics
  + Machine learning algorithms
  + Artificial intelligence
  + Decision trees
  + Deep learning
* Results
* The paper reviews and compares current research on air quality evaluation.
* It highlights observations on future research issues, challenges, and needs.
* The paper addresses the challenges of dynamic wind flow and time complexity.
* The paper proposes discovering the region of influence for air quality evaluation.
* The paper emphasizes the need for data quality and validation in air quality assessment.
* Conclusions
  + Real-time air quality monitoring and evaluation is desirable for future smart cities.
  + The paper reviews and compares current research on air quality evaluation.
  + Future research issues, challenges, and needs are highlighted.

10. Machine Learning-Based Prediction of Air Quality

* Intro
  + Air pollution is a global issue with harmful effects on health and the environment.
  + Air quality evaluation is crucial for monitoring and controlling pollution.
  + The paper focuses on developing prediction models for air quality index (AQI) levels.
  + Machine learning methods like AdaBoost, ANN, random forest, SVM, and stacking ensemble are used.
  + The stacking ensemble model consistently delivers superior performance for AQI predictions.
* Methods Used
  + Adaptive boosting (AdaBoost)
  + Artificial neural network (ANN)
  + Random forest
  + Stacking ensemble
  + Support vector machine (SVM)
* Results
  + The paper provides a general description of the dataset used.
  + The paper discusses the development of AQI prediction models.
  + The paper evaluates the performance of the AQI forecasting models.
* Conclusions
  + Applying artificial intelligence methods provides promising results for AQI forecasting.
  + Stacking ensemble and AdaBoost offer the best performance for target predictions.
  + SVM yields the worst results among all methods explored.
  + AdaBoost and stacking ensemble can outperform popular methods in the literature.
  + Prediction performance varies over different regions in Taiwan.
  + 95 confidence intervals for 1-h, 8-h, and 24-h forecast are calculated.
  + The 95 C.I. can provide a better reference to the decision-maker.

11. Time Series Analysis and Forecasting of Air Quality in India

Intro

* Paper analyzes air quality in India and effects of seasons and COVID-19.
* Extensive preprocessing of time series data for accurate results.
* PM 2.5 and PM 10 have greatest impact on air quality.
* Nationwide lockdown due to COVID-19 improved AQI levels.
* Forecasting algorithm Prophet used for highly accurate predictions.
* Comparative analysis of AQI for Delhi and Bengaluru.
* Different seasons and climates affect air quality measures.

Literature Review

* Previous studies evaluate pollutant concentration using different methods in Shanghai.
* Seasonal trends and variations in pollutant concentration are analyzed.
* COVID-19 lockdown has a positive impact on air quality.
* Time series-based forecasting can provide effective data on pollutant concentration.
* Different seasons and climates affect air quality measures in different locations.

Methods Used

* Missing data imputation using forward fill and backward fill techniques.
* Selection of imputation technique with the least mean absolute error.
* Resampling of data to obtain weekly, monthly, and quarterly data.
* Forecasting algorithm Prophet used for predicting monthly average air quality index.
* Comparative analysis of AQI for Delhi and Bengaluru.

Results

PM 2.5 and PM 10 have the greatest impact on air quality.

COVID-19 lockdown led to a substantial improvement in AQI levels.

Prophet algorithm accurately predicts monthly average air quality index.

Comparative analysis of AQI for Delhi and Bengaluru provides valuable insights.

Limitations

* Missing values in time series data affect accuracy of outputs.
* Discrepancies and discontinuity in time series data due to missing values.
* Limited focus on analysis of one factor affecting pollutant concentration.

Conclusions

* PM 2.5 and PM 10 have the greatest impact on air quality.
* NO and NO2 have the highest correlations with AQI.
* Forecasting air quality helps cities take preventive measures and plan ahead.
* Different seasons see an increase in certain pollutants.
* Analysis with the season as a parameter gives valuable insights.

12. Forecast Energy Consumption Time-Series Dataset using Multistep LSTM Models

* Intro
* Paper focuses on forecasting electricity consumption for the beLyfe monitoring system.
* Four multistep LSTM models are evaluated for accuracy and robustness.
* ConvLSTM model achieves high predictive accuracy and is computationally efficient.
* Short-term electricity forecasting is complex due to non-linear patterns.
* Deep neural network models, like LSTM, are effective for time-series forecasting.
* Literature Review
* LSTM model discussed in short-term load forecasting with acceptable accuracy.
* ResNet combined with LSTM to improve forecasting accuracy.
* LSTM-based deep learning framework for residential electricity consumption forecasting.
* ConvLSTM stacked autoencoders used for single-step time series prediction.
* Hybrid framework combining wavelet transformation with LSTM for electricity load forecasting.
* Multi-channel LSTM model incorporating power consumption, time location, and customer behavior.
* CNN-LSTM model frequently utilized for spatial and temporal feature extraction in load forecasting.
* Hybrid CNN-LSTM model proposed for residential energy consumption forecasting.
* Methods Used
* Four multistep LSTM models: vanilla LSTM, Bidirectional LSTM, Stacked LSTM, Convolutional LSTM
* Comparison experiment to evaluate performance in accuracy and robustness.
* Results
* Four multistep LSTM models were evaluated for forecasting electricity consumption.
* The ConvLSTM model achieved high predictive accuracy and was less computationally expensive.
* The ConvLSTM model outperformed the Bidirectional LSTM model in terms of computational time.
* The ConvLSTM model requires further improvement by incorporating meteorological factors.
* The multistep ConvLSTM model could be used for predicting monthly electricity consumption.
* Conclusions
* Electricity consumption forecasting is important for managing demand and cost.
* Four multistep LSTM models were evaluated for accuracy and robustness.
* The ConvLSTM model achieved high predictive accuracy and was computationally efficient.

13. A Comprehensive Review on Time Series Forecasting Techniques

* Intro
* Time series forecasting is used to predict future values based on historical data.
* It captures patterns, trends, and seasonality in data for accurate predictions.
* Steps include data collection, preprocessing, exploratory analysis, model selection, training, validation, forecasting, and evaluation.
* Techniques include ARIMA, exponential smoothing, neural networks, and Bayesian methods.
* Models are refined through iteration and continuous improvement.
* Time series forecasting provides valuable insights for decision-making in various domains.
* Literature review
* The paper provides a comprehensive review and comparative analysis of different time series forecasting techniques.
* It discusses traditional statistical methods such as ARIMA and Exponential Smoothing.
* It elaborates on the use of Neural Networks for capturing complex patterns.
* Bayesian methods are discussed for handling uncertainties and incorporating prior knowledge.
* The advantages and limitations of each technique are discussed.
* Real-world applications across various domains are highlighted.
* Method Used
* Exponential smoothing methods (Simple Exponential Smoothing, Holt's Linear Exponential Smoothing, Holt-Winters' Exponential Smoothing, Seasonal Exponential Smoothing, Double and Triple Exponential Smoothing)
* Autoregressive Integrated Moving Average (ARIMA)
* Seasonal ARIMA (SARIMA)
* Neural Networks
* Bayesian methods
* Prophet (a forecasting model)
* Results
* The paper provides a comprehensive review and comparative analysis of different time series forecasting techniques.
* It discusses traditional statistical methods like ARIMA and Exponential Smoothing.
* It elaborates on the use of Neural Networks for capturing complex patterns.
* Bayesian methods are discussed for handling uncertainties and providing probabilistic forecasting.
* The advantages and limitations of each technique are discussed.
* Real-world applications across various domains are highlighted.
* The paper empowers researchers and practitioners to make informed decisions regarding technique selection.

Limitations

* Computational complexity
* Data requirements
* Interpretability
* Presence of external factors or seasonality
* Conclusions
* Each technique has its advantages and limitations.
* The selection of an appropriate technique depends on specific requirements and characteristics of the dataset.
* Traditional statistical methods like ARIMA, SARIMA, and Exponential Smoothing provide a solid foundation for time series analysis.
* Bayesian methods are suitable when prior knowledge or expert opinions are available.
* Spectral analysis is best for frequency content and periodicities in data.
* State space models are suited for dynamic and uncertain processes.
* Neural networks excel at capturing complex patterns and non-linear relationships.

14.Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks

* Intro
* Multivariate time series forecasting is important in various domains.
* Traditional approaches fail to capture both long-term and short-term patterns.
* The paper proposes LSTNet, a deep learning framework for time series forecasting.
* LSTNet combines CNN and RNN to extract patterns and discover trends.
* LSTNet achieves significant performance improvements over baseline methods.

* Literature Review
* ARIMA models are popular but rarely used in high dimensional multivariate time series forecasting.
* VAR models are widely used but ignore dependencies between output variables.
* Linear regression models and Gaussian Processes have limitations in capturing complex relationships.
* LSTNet integrates neural network and autoregressive components for improved forecasting.
* Methods Used
* AR (autoregressive model)
* LRidge (vector autoregression model with L2 regularization)
* LSTNet (Long-and Short-term Time-series network)
* Result
* LSTNet achieved significant performance improvements over state-of-the-art baseline methods.
* LSTNet outperformed RNN-GRU by 9.2, 11.7, and 22.2 in RSE metric on Solar-Energy, Traffic, and Electricity datasets respectively.
* LSTNet consistently enhanced performance on datasets with periodic patterns.
* LSTNet-attn yielded considerable improvement over LSTNet-skip when periodic pattern is not clear.
* LSTNet performed comparably with AR and LRidge on the Exchange-Rate dataset.
* Conclusions
* Proposed LSTNet significantly improved state-of-the-art results in time series forecasting.
* LSTNet captures both short-term and long-term repeating patterns in data.
* LSTNet combines both linear and non-linear models for robust prediction.
* Future research directions include automatic selection of skip length and integration of rich attribute information.

15.Incorporating Time-Series Forecasting Techniques to Predict Logistics Companies’ Staffing Needs and Order Volume

* Intro
* Accurate order volume prediction is crucial for logistics companies' resource allocation.
* Time-series analysis and machine learning can optimize resource planning and management.
* Existing methods have limitations in capturing dynamic logistics industry factors.
* This study evaluates four time-series analysis methods: SARIMAX, ARIMA, AR, and LSTM.
* The study aims to identify the most accurate method for predicting order volumes.
* Data from a shipping company in UAE, KSA, and KWT is used for evaluation.
* SARIMAX model outperformed other methods in predicting order volumes and trends.
* Literature Review
* Literature review focuses on time-series forecasting models and machine learning techniques.
* Singha and Panse compared machine learning algorithms for time-series forecasting.
* Lee et al. proposed a multivariate LSTM approach for container volume forecasting.
* Ferretti et al. compared deep learning models for container throughput forecasting.
* Clarabelle and Gatc used SARIMA to predict the number of passengers on a ship.
* Li and Wei used LSTM networks to predict logistics needs post-epidemic.
* Fadda et al. used machine learning and optimization techniques for vehicle fleet forecasting.
* Bruni et al. proposed a machine learning heuristic for last-mile delivery optimization.
* Xu et al. developed the Informer model for power load forecasting.
* Method Used
* SARIMAX
* ARIMA
* LSTM
* AR
* Results
* Time-series forecasting techniques were used to predict order volumes in logistics companies.
* SARIMAX model outperformed other methods in predicting order volumes and trends.
* The study compared the performance of four different time-series analysis methods.
* The predictions were based on data collected from a shipping company.
* The paper achieved its objective of identifying reliable and accurate forecasting methods.
* Limitations
* Inability to use data from 2020 and earlier due to inaccuracy.
* Uncertainty about optimal parameter range for models.
* Difficulty in incorporating external variables like holidays and sales seasons.
* Challenges in combining data from different countries.
* Time-consuming process of downloading, analyzing, and arranging large amount of data
* Conclusions
* SARIMAX is the most accurate model for predicting order volumes.
* Operational efficiency helps estimate time and manpower required for packing.
* Formula provided for predicting staffing needs based on order volume.
* Further research needed to enhance understanding and improve accuracy.

16.Sequence to Sequence Learning with Neural Networks

* Intro
* DNNs are powerful models but can't map sequences to sequences.
* This paper presents a general approach using LSTM for sequence learning.
* LSTM achieves a BLEU score of 34.8 on English to French translation task.
* LSTM's performance improves when reversing the order of source sentences.
* LSTM outperforms a phrase-based SMT system on the translation task.
* Literature Review
* Previous work includes using RNN-Language Models (RNNLM) and Feedforward Neural Network Language Models (NNLM) for machine translation.
* Researchers have explored incorporating source language information into NNLM.
* Kalchbrenner and Blunsom mapped input sentences to vectors using convolutional neural networks.
* Cho et al. used LSTM-like RNN architecture to map sentences into vectors.
* Bahdanau et al. used a neural network with attention mechanism for direct translations.
* Pouget-Abadie et al. addressed memory problem by translating pieces of source sentences.
* Hermann et al. used feedforward networks to represent inputs and outputs.

Method Used

* General end-to-end approach to sequence learning
* Multilayered Long Short-Term Memory (LSTM) for mapping input sequence
* Deep LSTM for decoding target sequence
* Rescoring the baseline 1000-best list with LSTM
* Reversing the order of words in source sentences to improve performance
* Ensemble of 5 reversed LSTMs for rescoring the baseline 1000-best list
* Oracle Rescoring of the Baseline 1000-best lists

Result

* LSTM achieves a BLEU score of 34.8 on English to French translation task.
* LSTM's BLEU score increases to 36.5 when used to rerank hypotheses.
* LSTM outperforms phrase-based SMT baseline on large scale MT.
* Limitations
* The LSTM ensemble does not outperform the best WMT'14 system.
* The LSTM's performance is not improved on non-reversed translation problems.
* The LSTM's vocabulary is limited.
* Conclusions
* Large deep LSTM outperforms standard SMT-based system on MT task.
* Reversing words in source sentences improves LSTM's performance.
* LSTM can correctly translate very long sentences.
* LSTM learns to map variable length input sentences into fixed-dimensional vector representation.
* LSTM is aware of word order and invariant to active/passive voice.

17. A LITERATURE REVIEW ON TIME SERIES FORECASTING METHODS.

* Intro
* Literature review on time series forecasting methods
* Explains working of time series forecasting methods
* Discusses advantages and disadvantages of time series forecasting
* Reviews approaches and applications of different methods used in time series forecasting
* Goal is to increase knowledge regarding time series forecasting and its methods
* Literature Survey
* The paper reviews time series forecasting methods and their working.
* It discusses the advantages and disadvantages of time series forecasting.
* The paper explores the approaches and applications of different forecasting methods.
* The goal is to increase knowledge about time series forecasting and its methods.
* Methods Used
* Autoregression (AR)
* Moving Average (MA)
* Autoregressive Moving Average (ARMA)
* Autoregressive Integrated Moving average (ARIMA)
* Seasonal Autoregressive Integrated Moving Average (SARIMA)
* Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX)
* Vector Autoregression (VAR)
* Vector Autoregression Moving Average (VARMA)
* Vector Autoregression Moving Average with Exogenous Regressors (VARMAX)
* Simple Exponential Smoothening (SES)
* Holt's Winter Exponential Smoothening (HWES)
* Results
* The paper discusses time series forecasting methods and their working.
* It mentions the advantages and disadvantages of time series forecasting.
* The paper explores different approaches and applications of time series forecasting methods.
* The concept of stationarity is discussed and its importance in machine learning models.
* SARIMA models were found to perform better than ARIMA models in long-term runoff forecasting.
* SARIMA models were sensitive to parameter changes and could result in poor performance.
* Limitations
* Some methods do not perform well with seasonal data.
* Some methods do not perform well with trends in the data.
* The performance of different methods depends on the parameters used.
* The concept of stationarity is discussed but not the best performing method.
* Statistically sophisticated methods do not necessarily provide more accurate forecasts.
* The accuracy of the methods depends on the length of the forecasting horizon.
* Conclusions
* Different time series forecasting methods have varying results depending on the use case and data.
* Each model is specific to its use case and the data involved.
* Time series forecasting considers natural factors such as trends and seasons.
* New algorithms may be developed to handle both seasonality and trends.
* Stationarity concept helps in machine learning models and making data stationary.
* Statistically sophisticated methods do not necessarily provide more accurate forecasts.
* Combining multiple methods can outperform individual methods.
* The accuracy of methods depends on the length of the forecasting horizon.