

Forecasting Trends in Technological Innovations with Distortion-Aware Convolutional Neural Networks

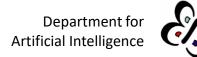
Slovenian KDD 2023

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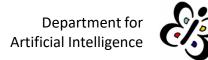
This work was supported by the European Union through enRich-MyData EU HE project under grant agreement No 101070284.





Introduction



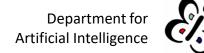




Example: Number of Patents Related to "Neural Networks"



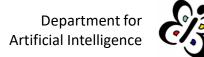






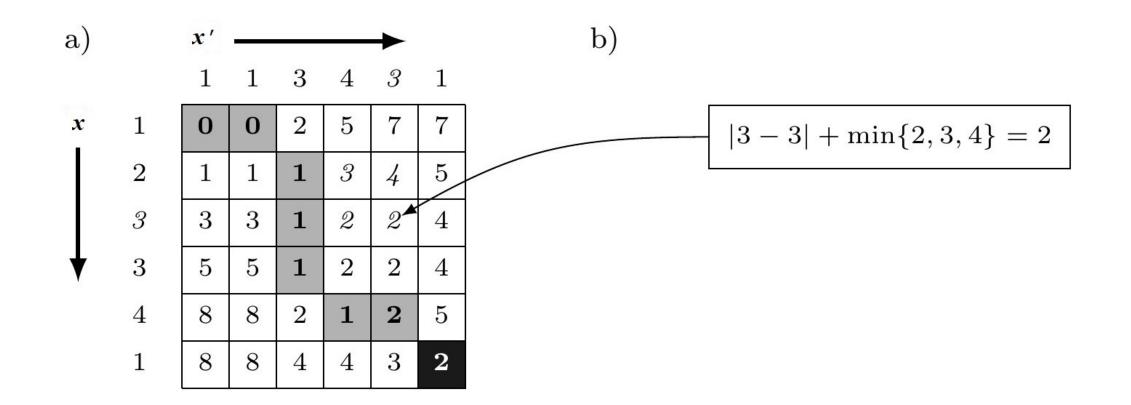
Background



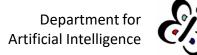




Dynamic Time Warping

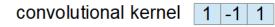


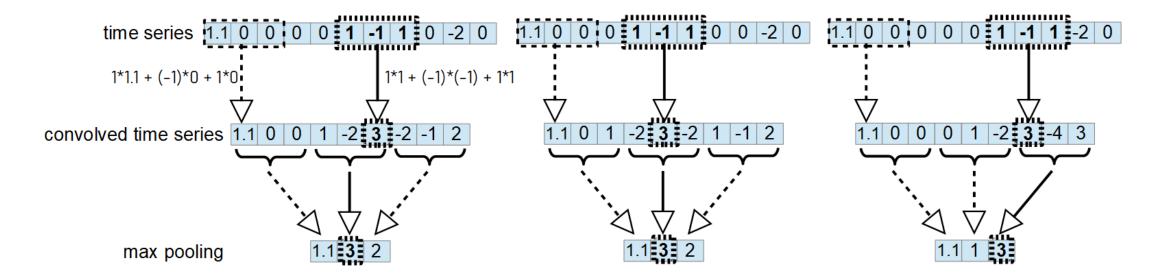


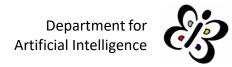














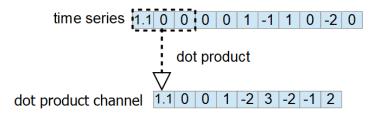


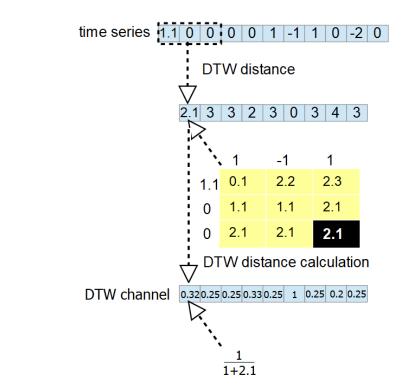
Jožef Stefan

Institute

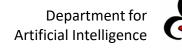
Distortion-aware Convolution

convolutional kernel 1 -1 1





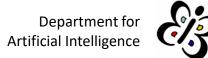
Krisztian Buza. 2023. Time Series Forecasting with Distortion-Aware Convolutional Neural Networks. In 9th SIGKDD International Workshop on Mining and Learning from Time Series.





Problem Formulation







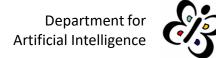
Problem Formulation

Given an observed time series $x = (x_1, \ldots, x_l)$ of length l, we aim at predicting its subsequent h values $y = (x_{l+1}, \ldots, x_{l+h})$. We say that h is the forecast horizon and y is the target. Furthermore, we assume that a dataset D is given which contains n time series with the corresponding target:

$$D = \{ (x^{(i)}, y^{(i)})_{i=1}^n \}.$$
(1)

We use D to train neural networks for the aforementioned prediction task. We say that $x^{(i)}$ is the input of the neural network.

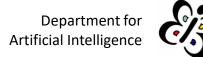






Our Approach



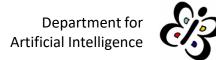




Our Approach

• DCNN: Convolutional Neural Network with Distortion-aware convolution

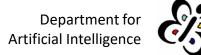






Experiments



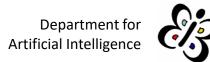




Data

- Time series: number of (a) granted patents and (b) patent applications per month between January 1980 and December 2022.
- Selected topics:
 - Image or video recognition
 - Neural networks
 - Natural Language Processing
 - Artificial Intelligence
- We considered the patents separately for the most significant jurisdictions:
 (a) United States of America, (b) China, (c) Korea, (d) Japan and (e) Europe,
 (f) all jurisdictions.



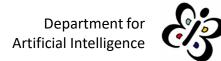




Experimental Settings

- Forecast horizon: h = 6 months, input: previous 36 month
- Training data: 1980...2018
- Test data: 2019...2022
- Baseline: Convolutional network with "usual" convolution (CNN)
- Training loss: MSE, Adam optimizer, learning rate of 10⁻⁵, batch size: 16
- Implementation: <u>https://github.com/kr7/dcnn-forecast</u> (using publicly available datasets)
- Evaluation metrics:
 - mean squared error (MSE)
 - mean absolute error (MAE)







Funder Table 1: Mean absolute error (MAE) and root mean squared er-the Eur ror (RMSE) for forecasting the time series of granted patents in case of our approach (DCNN) and the baseline (CNN). Lower values indicate better performance.

	juris-	RMSE		MAE	
topic	diction	CNN	DCNN	CNN	DCNN
image or	US	165.9	106.0	131.2	92.7
video	China	405.8	320.9	323.87	217.6
recognition	Korea	13.9	27.7	12.4	19.9
	Japan	55.9	49.8	39.9	37.8
	Europe	34.5	34.7	32.3	32.9
	ALL	494.7	399.6	416.8	341.3
neural	US	10.7	9.1	9.4	7.9
networks	China	5.6	5.5	3.8	3.7
	Korea	6.3	2.3	5.4	7.9 3.7 2.1 2.0
	Japan	3.5	2.9	2.5	2.0
	Europe	2.7	1.6 8.3	2.2	1.2 6.7
	ALL	7.6	8.3	6.3	6.7
natural	US	19.7	15.1	14.8	12.0
language	China	57.1	47.0	41.6	41.7
processing	Korea	14.2	8.5	13.1	7.3
	Japan	11.8	10.7	9.5	7.3 7.3 2.7
	Europe	4.8	3.0	3.5	2.7
	ALL	67.0	45.7	59.5	35.5
ALL	US	270.2	216.9	224.1	196.4
	China	870.2	1108.8	763.2	998.1
	Korea	56.6	138.3	53.8	129.4
	Japan	124.8	132.0	81.4	89.9
	Europe	85.8	69.2	82.1	65.9
	ALL	1045.1	1129.1	<u>929.2</u>	964.6

Table 2: Mean absolute error (MAE) and root mean squared error (RMSE) for forecasting the time series of patent applications in case of our approach (DCNN) and the baseline (CNN). Lower values indicate better performance.

	juris-	RMSE		MAE	
topic	diction	CNN	DCNN	CNN	DCNN
image	US	188.2	177.1	170.2	163.3
or video	China	3405.0	1061.7	3375.4	1042.3
recognition	Korea	128.9	70.8	99.7	69.4
	Japan	103.8	106.4	87.1	66.1
	Europe	51.9	55.5	45.0	49.4
	ALL	3641.9	2110.5	3627.3	2027.8
neural	xUS	79.8	15.3	76.9	12.7
networks	China	21.2	20.8	16.8	19.0
	Korea	44.6	6.8	43.7	6.2
	Japan	13.9	7.1	13.5	4.8
	Europe	15.8	5.9	14.9	4.4
	ALL	267.7	45.6	262.7	38.6
natural	US	64.1	68.7	55.5	64.6
language	China	418.9	318.2	363.6	289.3
processing	Korea	35.1	23.4	29.7	21.0
	Japan	16.7	18.7	10.5	10.8
	Europe	11.2	14.3	9.7	11.2
	ALL	298.1	543.0	226.9	489.3
ALL	US	532.3	329.1	458.9	311.3
	China	6443.7	2784.2	6239.0	2386.5
	Korea	405.4	216.8	340.2	180.8
	Japan	224.8	228.1	159.1	128.6
	Europe	130.0	163.5	97.5	121.3
	ALL	5445.1	3355.8	5009.0	2547.0



Conclusions

- Overall, DCNN performs better than CNN
- Combination of CNN and DCNN may be a promising direction of future work
- The presented approach may be simply generalized to multivariate time series using multivariate DTW

Krisztian Antal Buza. 2011. Fusion methods for time-series classification. PhD thesis at the University of Hildesheim (2011).



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