

Neural networks and state estimation

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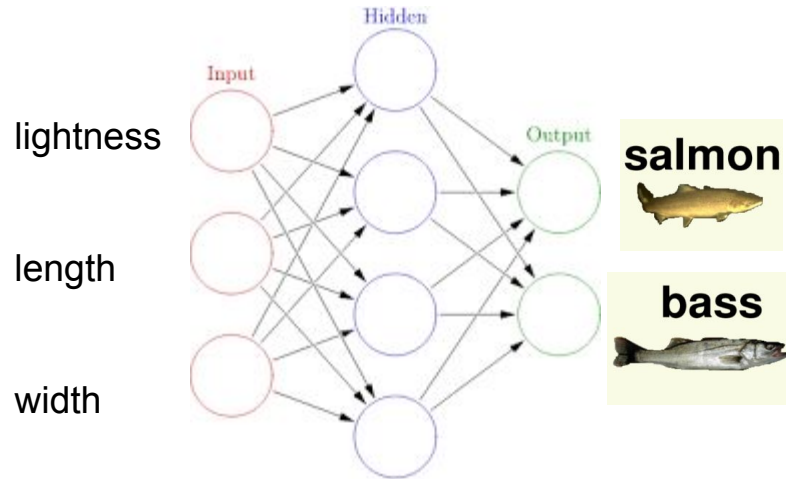
Agenda



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- Introduction to neural network
- Recurrent neural networks for electric grid analysis
 - Problem statement
 - Method description
 - Experimental result
 - Conclusion
- Neural networks for robust spectra reconstruction
 - Problem statement
 - Method description
 - Experimental result
- Conclusion

Introduction to neural network



→ : $\text{act}(w \cdot x + b)$

Activation Functions

Sigmoid
 $\sigma(x) = \frac{1}{1 + e^{-x}}$



tanh
 $\tanh(x)$



ReLU
 $\max(0, x)$



Leaky ReLU
 $\max(0.1x, x)$

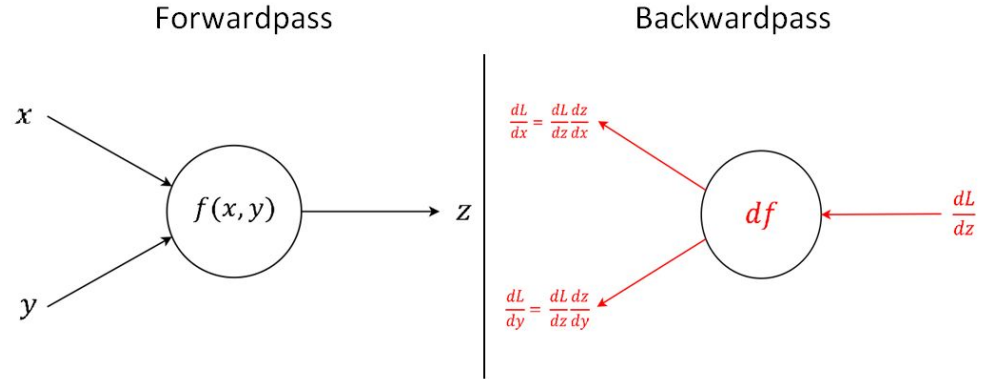
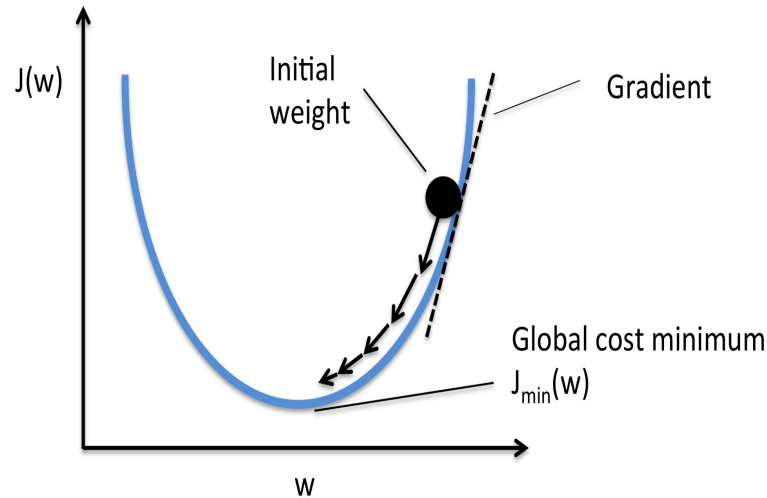


Maxout
 $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU
 $\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$

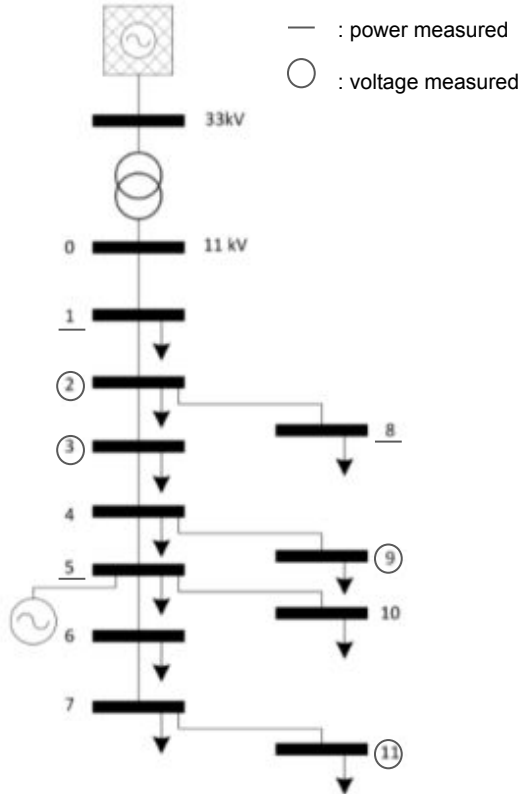


Introduction to neural network



RNNs for electric grid analysis

Problem Statement



Goal:

- Online state estimation with incomplete measurement.
 - Power Value

RNNs for electric grid analysis

Method Description

- State equation:

$$\mathbf{x}_k = f(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{w}_{k-1})$$

- Measurement equation:

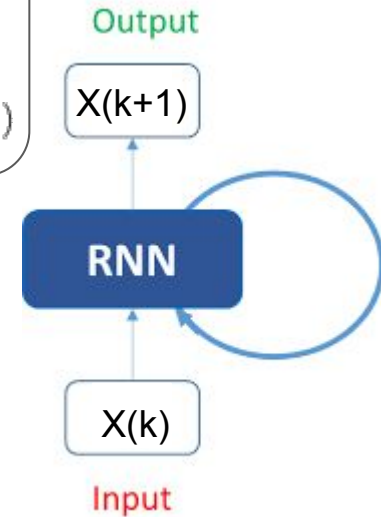
$$\mathbf{z}_k = h(\mathbf{x}_k, \mathbf{v}_k)$$

Case 1: one-layer NN

$$\mathbf{x}(k+1) = \mathbf{w}_k * \sigma(\mathbf{x}(k)) + \mathbf{g}(k)$$

Case 2: two-layer NN

$$\mathbf{x}(k+1) = \mathbf{w}_{2,k} * \sigma[\mathbf{w}_{1,k} * \sigma(\mathbf{x}(k))] + \mathbf{g}(k)$$



RNNs for electric grid analysis

Method Description

Learning Method:

- Joint Estimation: EKF for weight parameter + EKF for state (power)
- Kalman Filter: Using Extended Kalman Filter to update \hat{w} and \hat{x} alternatively

Algorithm (Pseudocodes):

- ❑ Initialize w_0, x_0
- ❑ For k in timepoints:
 - ❑ A priori forecast: $w_f(k) = w(k-1)$
 - ❑ For i in itersteps:
 - ❑ KF updating $\hat{w}(k)$
 - ❑ When updating converges, break
 - ❑ A priori forecast: $x_f(k) = \text{RNN}(\hat{w}(k), x(k-1))$
 - ❑ For j in itersteps:
 - ❑ KF updating $\hat{x}(k)$
 - ❑ When updating converges, break
 - ❑ $\hat{S}(k) = S_m(k) + \hat{x}(k)$

RNNs for electric grid analysis

Experimental Results

iter		200	400	500	600	800	1000
Joint	RNN-1	0.2724	0.2694	0.2693	0.2704	0.2764	0.2849
	RNN-2	0.2705	0.2659	<u>0.2645</u>	0.2647	0.2732	0.3008

Table 1: Mean Squared Error (10^{-2}) of estimation results using 1-layer RNN and 2-layer RNN

iter		400	500	550	600
RNN-2	Adaptive AR[1]	4.2785			
	Only State	0.4245			
	Only Weight	0.2664	0.2650	0.2648	0.2650
	Joint	0.2659	0.2645	<u>0.2644</u>	0.2647

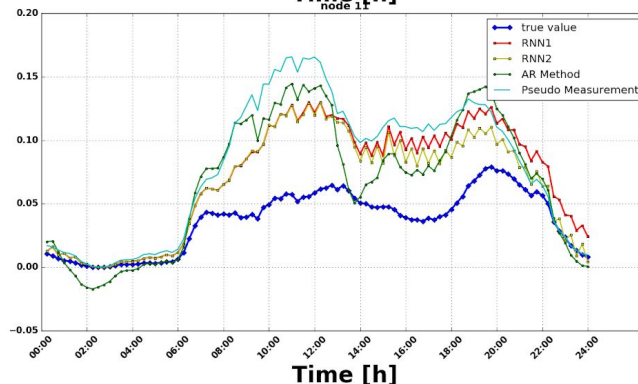
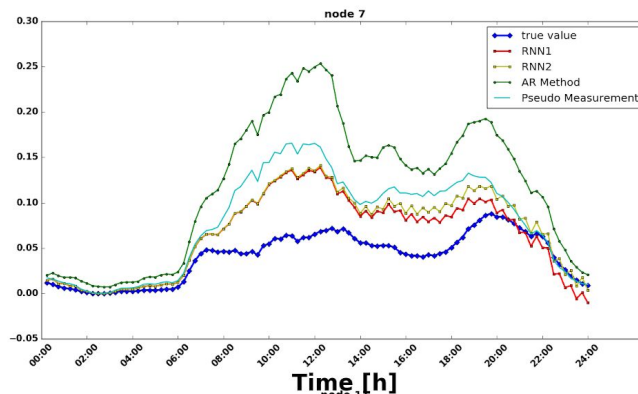
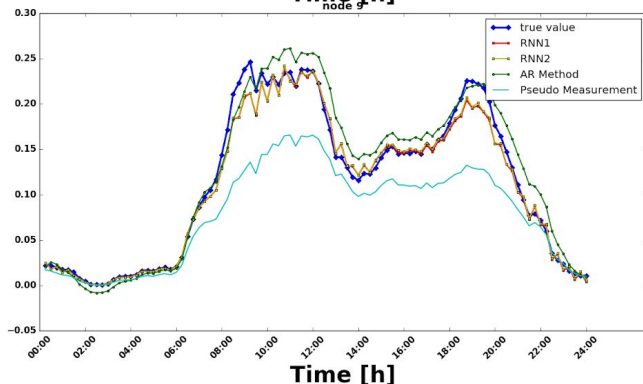
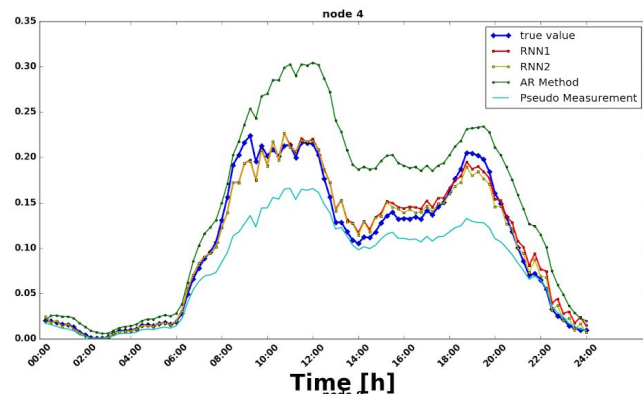
Table 3: Mean Squared Error (10^{-2}) of estimation results using only-state method, only-weight method and Joint method

	Time/s
RNN-1	0.6223
RNN-2	0.8041

Table 2: Computation time for one time points' estimation

RNNs for electric grid analysis

Experimental Results



Power measured at:
[1, 5, 8]
Voltage measured at:
[2, 3, 9, 11]

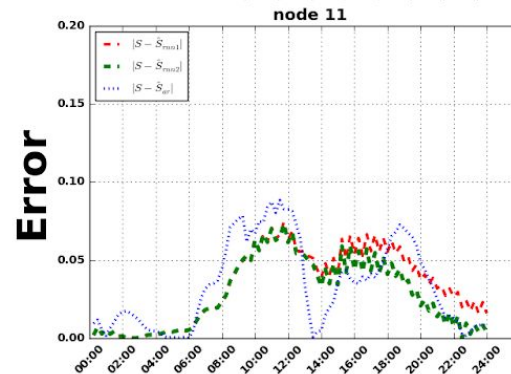
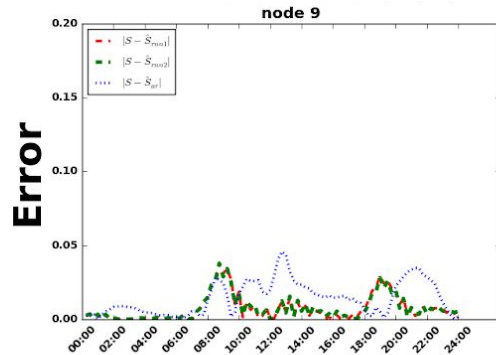
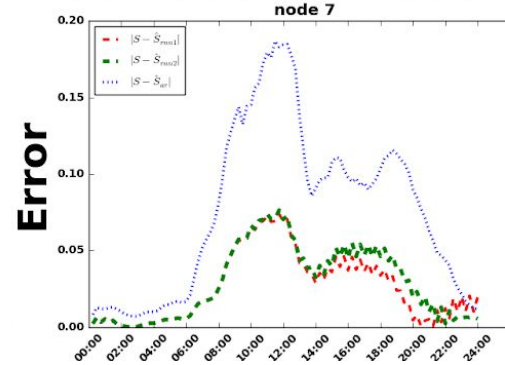
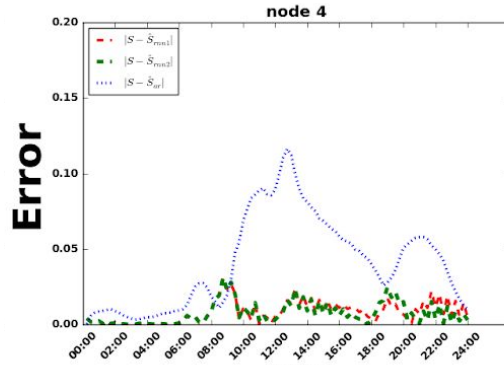
Power to be estimated:
[2, 3, 4, 6, 7, 9, 10, 11]

RNNs for electric grid analysis

Experimental Results

Power measured at:
[1, 5, 8]
Voltage measured at:
[2, 3, 9, 11]

Power to be estimated:
[2, 3, 4, 6, 7, 9, 10, 11]



Mean Absolute Error of estimation (node 4, node 7, node 9, node 11) using AR_Adaptive, RNN1 and RNN2 method

RNNs for electric grid analysis

Experimental Results

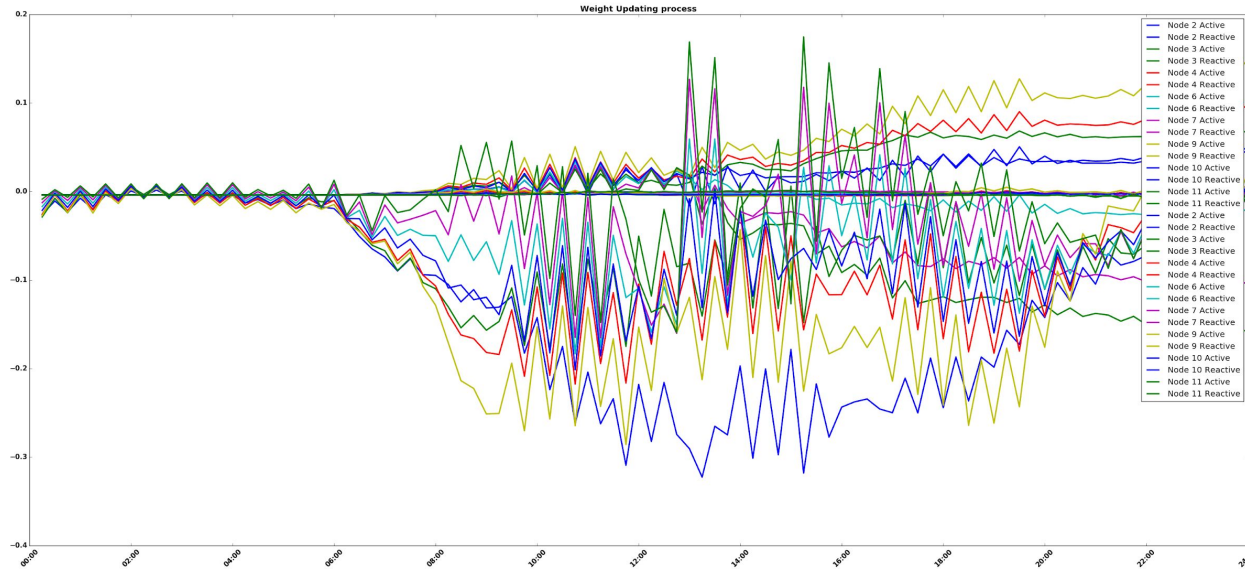


Fig 1: Updating process of weights in the 1st layer.

8 nodes' active and reactive powers need to be estimated.

2 layer RNNs.

Parameter numbers:
 $8 \times 2 \times 2 = 32$

RNNs for electric grid analysis

Experimental Results



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Two edge cases:

Power measured at:

[1]

Voltage measured at:

[2,3,4,5,6,7,8,9,10,11]

Power to be estimated:

[2,3,4,5,6,7,8,9,10,11]

Power measured at:

[1, 3, 4, 5, 6, 7, 8, 9, 10, 11]

Voltage measured at:

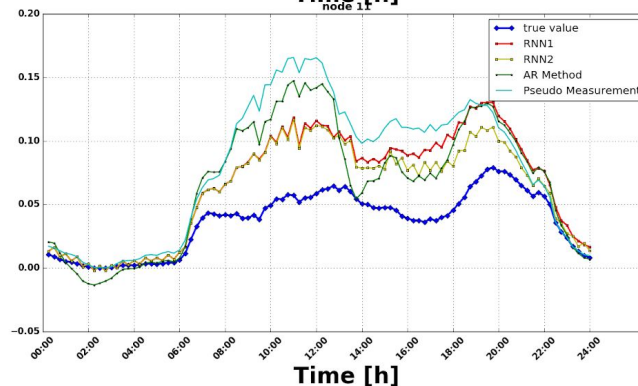
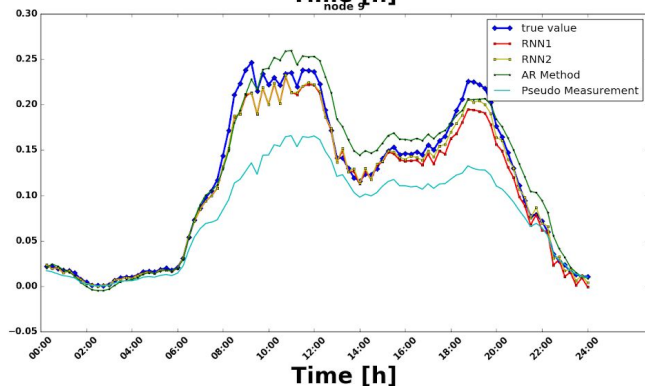
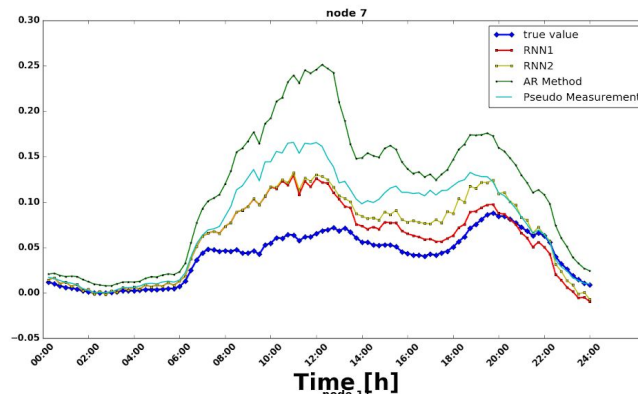
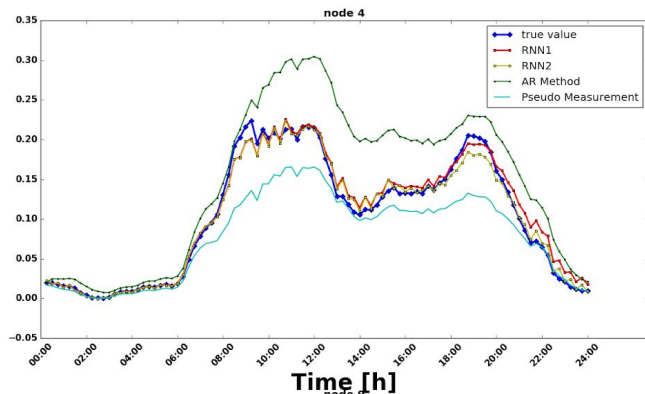
[2]

Power to be estimated:

[2]

RNNs for electric grid analysis

Experimental Results

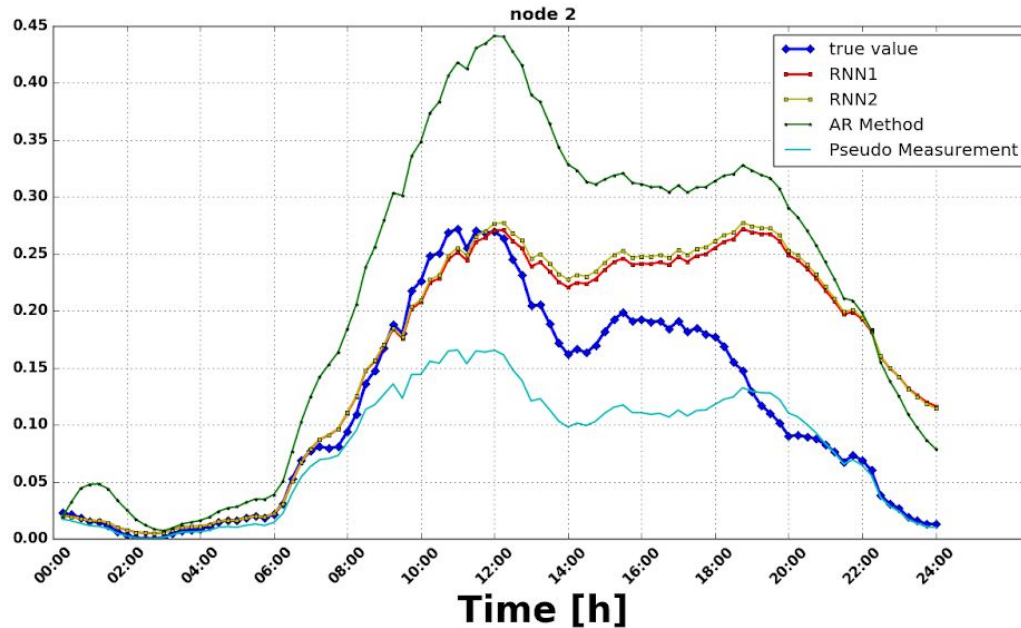


Power measured at:
[1]
Voltage measured at:
[2,3,4,5,6,7,8,9,10,11]

Power to be estimated:
[2,3,4,5,6,7,8,9,10,11]

RNNs for electric grid analysis

Experimental Results



Power measured at:
[1, 3, 4, 5, 6, 7, 8, 9, 10, 11]
Voltage measured at:
[2]

Power to be estimated:
[2]

RNNs for electric grid analysis

Conclusion

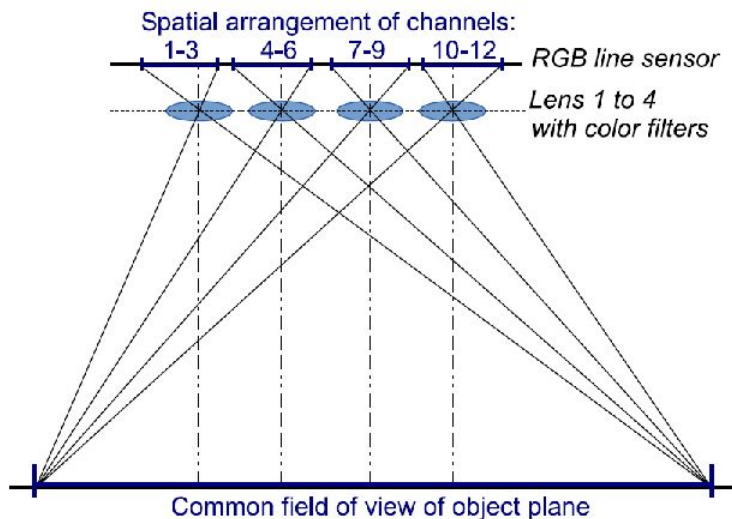


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- RNN-based estimation method can achieve great improvement with respect to the state-of-the-art.
- 2-layer RNN is slightly better than 1-layer RNN on this estimation task.
- RNN-based joint estimation is slightly better than RNN-based single estimation on this task.

NNs for robust spectra reconstruction

Problem statement



Reflectance spectra: 380~730nm

Camera response: 12 channel

Dataset description:

240 samples

sp: (240,351)

cr: (240,12)

→
split

180 samples for training

sp_train: (180,351)

cr_train: (180,12)

60 samples for testing:

sp_test: (60,351)

cr_test: (60,12)

NNs for robust spectra reconstruction

Method description

sp: (180,351)
cr: (180,12)

Linear
kernel

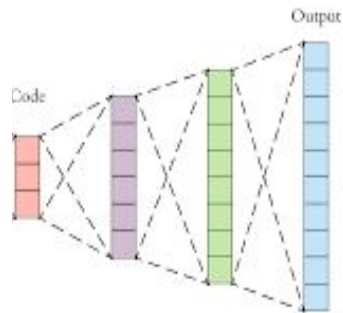
tr: (12,351)

Gaussian
kernel

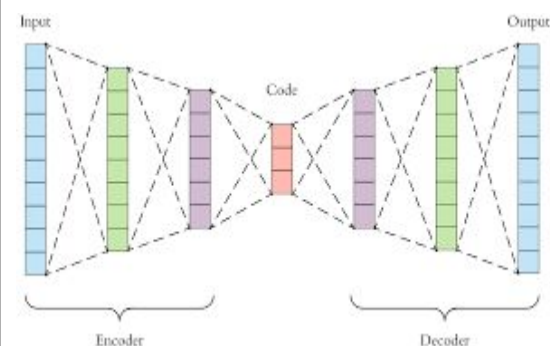
$tr = pinv(cr) * sp$

Logarithmic
kernel

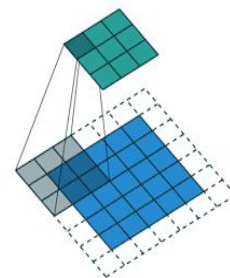
Pseudo-inverse Kernel Regression



Simple Neural Networks



Autoencoder

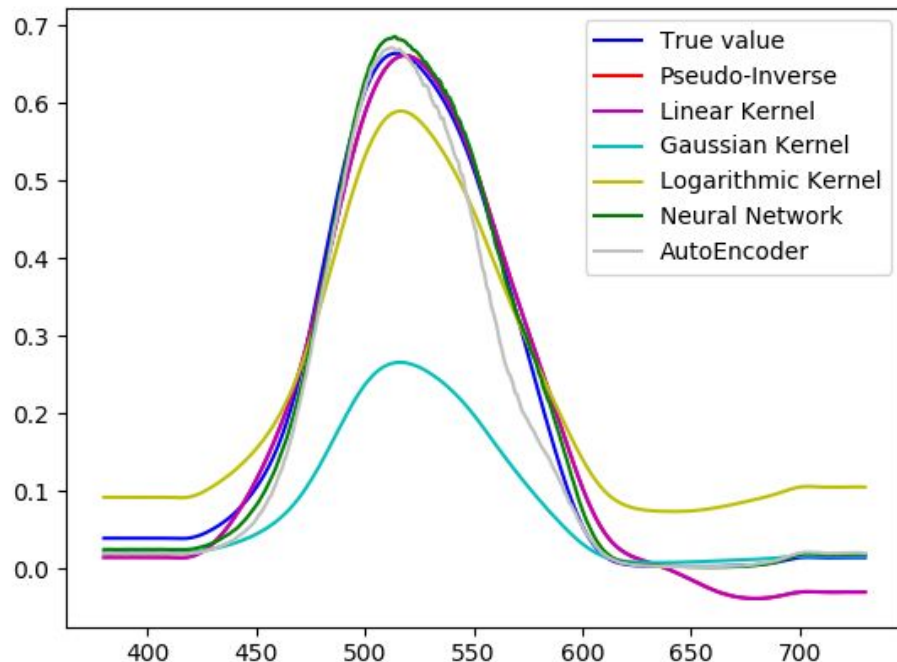


CNNs

NN-based methods

NNs for robust spectra reconstruction

Experimental Results



Noise: $N(\mu, \sigma^2)$

Noise	$\sigma=50$
pseudo-inverse	3.47E-06
linear kernel	3.47E-06
gaussian kernel	0.004006324995
logarithmic kernel	3.51E-05
NN	3.38E-06
Autoencoder	5.86E-06

Table 3: Average RMSE of reconstructions using different estimation method

NNs for robust spectra reconstruction

Experimental Results

Conclusion:

- Neural Network method can achieve the best results on spectra reconstruction, especially when the noise exists in the camera system. NN is a robust method.

Final Conclusion

- Neural Network method can learn the model from the data itself.
- NN is useful when the model is unknown or the model is complicated.

Thank you!



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