Towards Bringing Together Numerical Methods for Technology Partial Differential Equation and Deep Neural Networks

State of the Art, Supervisor - Markus Hoffmann Stanislav Arnaudov | December 8, 2019



Problem definition and motivation



Partial differential equation (PDEs)

- used in simulations
- solutions have image representation
- hard to solve numerically

Goal: solve PDEs based on their image representation

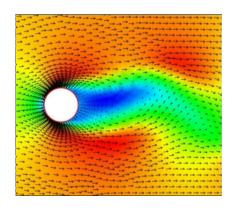


Figure: Flow Simulation¹

Motivation CNNs for image processing ●○○○ ○○○○ CNNs for numerical applications

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^{1&}quot;Team for Advanced Flow Simulation and Modeling", Professor Tayfun E. Tezduyar, Sunil Sathe

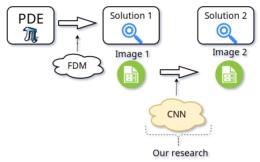
Problem definition and motivation



Convolutional neural networks (CNNs)

- hot topic in recent years
- impressive results in image processing

Idea: Use CNNs for the image representation of PDEs.





General Goals



CNNs

PDEs

Solve PDEs through their image representation using CNNs.

- efficiency
- acceptable error
- better running time

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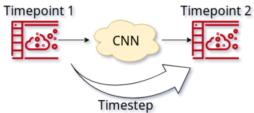
Important Questions



ONNs for image-to-image mapping?



② CNNs for numerical simulations?







We focus on an area where CNNs show good results:

- Image Segmentation
 - pixelwise decision about a class belonging
 - a new image is generated







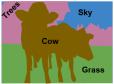


Figure: Image Segmentation²

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²"Exploring Computer Vision in Deep Learning: Object Detection and Semantic Segmentation", Long et al., SAS Institute Inc. 4 D > 4 B > 4 B > 4 B >



Image segmentation

- "Fully Convolutional Networks for Semantic Segmentation"
 - Encoder-Decoder Architecture
 - Only convolutional layers

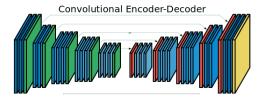


Figure: The encoder-decoder network

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³Jonathan Long, Evan Shelhamer, and Trevor Darrell. "Fully Convolutional Networks" for Semantic Segmentation". In: CoRR abs/1411.4038 (2014). arXiv: 1411.4038. URL: http://arxiv.org/abs/1411.4038. 4 D > 4 A > 4 B > 4 B >



Image segmentation

- "Semantic Segmentation using Adversarial Networks"
 - Generative Adversarial Networks⁵

CNNs for image processing

■ The Discriminator Network enforces contagiously segmented regions

http://papers.nips.cc/paper/5423-generative-adversarmal-nets.pdf. 📱

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⁴Pauline Luc et al. "Semantic Segmentation using Adversarial Networks". In: *CoRR* abs/1611.08408 (2016). arXiv: 1611.08408. URL: http://arxiv.org/abs/1611.08408.

⁵Ian Goodfellow et al. "Generative Adversarial Nets". In: *Advances in Neural Information Processing Systems 27.* Ed. by Z. Ghahramani et al. Curran Associates, Inc., 2014, pp. 2672–2680. URL:



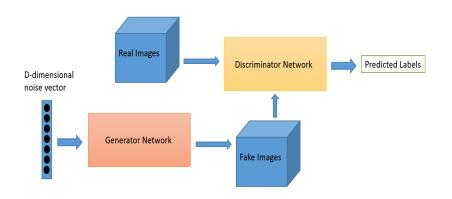


Figure: Generative Adversarial Network⁶

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Semantic Image Synthesis

- "Semantic Image Synthesis with Spatially-Adaptive Normalization"
 - Segmentation in reverse



Figure: Example of "reversed image segmentation"

http://arxiv.org/abs/1903.07291.

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⁷Taesung Park et al. "Semantic Image Synthesis with Spatially-Adaptive Normalization". In: CoRR abs/1903.07291 (2019). arXiv: 1903.07291. URL:



Long standing interest in bringing together neural networks and formal mathematics.

- It is shown to be possible "Performing basic mathematics with neurons/nets" (2002)8
- Even for PDEs "Artificial Neural Networks for Solving Ordinary and Partial Differential Equations" (1998)9

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⁸Richard Neville. "Performing basic mathematics with neurons/nets: Part I". In: vol. 1. Feb. 2002, pp. 589-594. ISBN: 0-7803-7278-6. DOI: 10.1109/IJCNN.2002.1005538.

⁹I. E. Lagaris, A. Likas, and D. I. Fotiadis. "Artificial neural networks for solving ordinary and partial differential equations". In: IEEE Transactions on Neural Networks 9.5 (1998), pp. 987-1000. ISSN: 1045-9227. DOI: 10.1109/72.712178, □ > < □ > < ≧ > < ≧ >



Nowadays CNNs are applied to complex physical simulations.

- CNNs for calculating physical properties of objects in simulations
- CNNs in flow simulation





- "Learning Soft Tissue Behavior of Organs for Surgical Navigation with Convolutional Neural Networks"
 - Prediction for how organs in the human body move during operation
 - Encoder-Decoder Architecture

CNNs for image processing

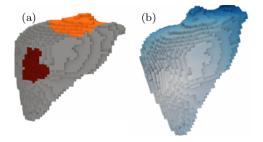


Figure: Given and predicted displacement of an organ

1904.00722. URL: http://arxiv.org/abs/1904.00722.

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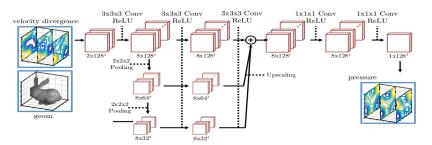
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¹⁰Micha Pfeiffer et al. "Learning Soft Tissue Behavior of Organs for Surgical Navigation with Convolutional Neural Networks". In: *CoRR* abs/1904.00722 (2019). arXiv:



- "Accelerating Eulerian Fluid Simulation With Convolutional Networks"
 - CNN for predicting fluid-flow
 - Calculate pressure given velocity divergence and geometry



http://arxiv.org/abs/1607.03597.

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¹¹Jonathan Tompson et al. "Accelerating Eulerian Fluid Simulation With Convolutional Networks". In: *CoRR* abs/1607.03597 (2016). arXiv: 1607.03597. URL:

Conclusion



To reiterate

- Problem: Solve PDEs
- Approach: Use CNNs for image-to-image mapping
- Goal: Efficiency and acceptable error

The conducted research illustrates:

- A research gap
- Evidence suggesting the proposed method is viable
- Typical CNN architectures that should be considered



Thank you for your attention.



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Questions?

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