Use of Machine Learning and GPU computing to study Lattice Boltzmann Methods for fluid flow simulations

Raghuvir Reddy Jonnagiri[1]
Dr. Ephraim Gutmark[2]

[1]Graduate student, Department of Aerospace Engineering, University of Cincinnati, OH 45221
[2]Distinguished Professor, Department of Aerospace Engineering, University of Cincinnati, OH 45221

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Research Motivation

To study the feasibility of application of machine learning advances in fluid flow simulations. GPUs are used to accelerate the data collection.

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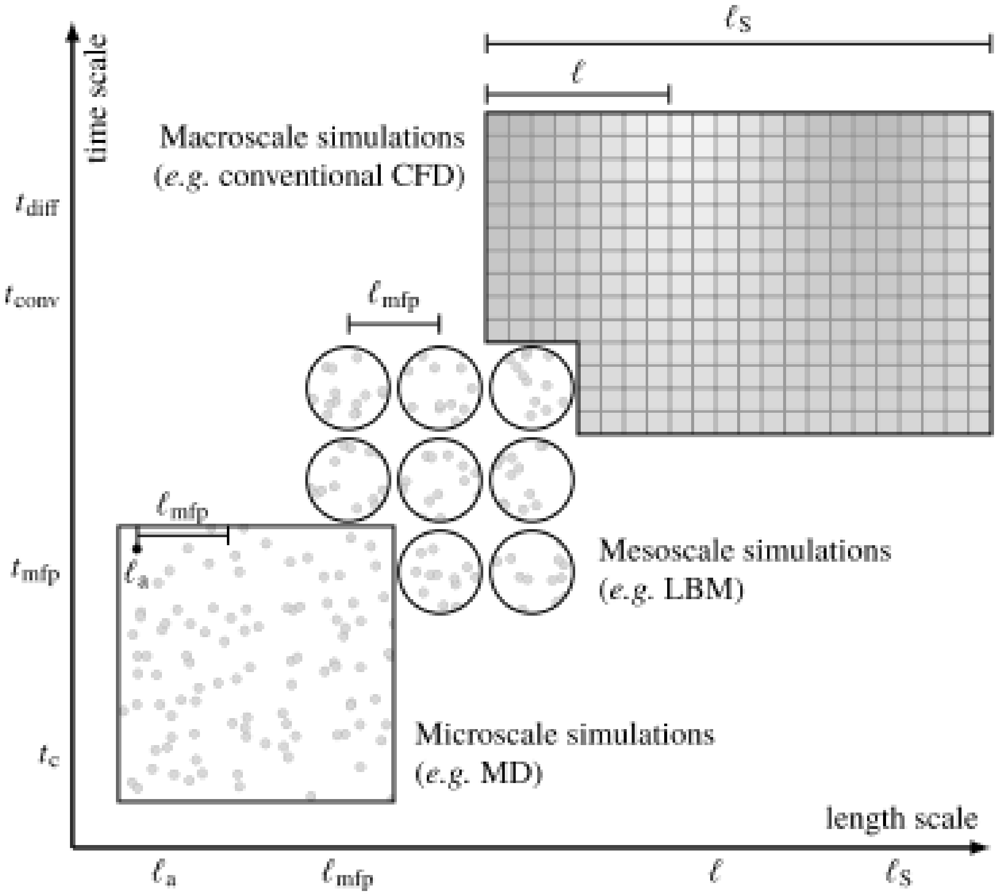
Overview

- Why Lattice Boltzmann Methods ?
- How effective is a GPU ?
- What can machine learning do ?

What is Lattice Boltzmann Method ?



Length and Time scales in Fluid Dynamics
Lattice Boltzman Methods – Principles and Practice, Tim Krueger et. al., 2016

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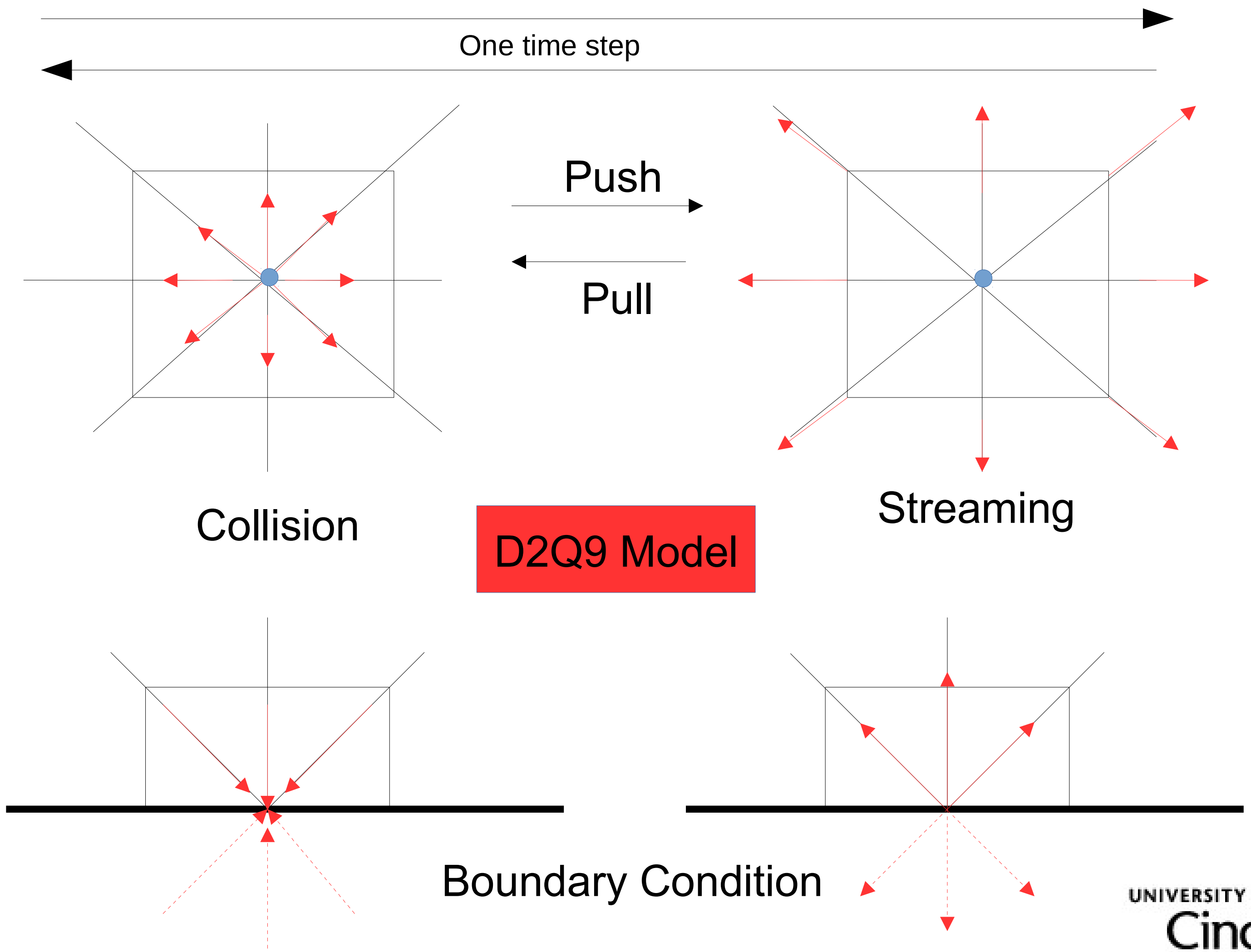
Lattice Boltzmann Methods - Concept



Lattice Boltzmann Methods - Mathematics

Collision : $$f_i^\star(\boldsymbol{x},t) = f_i(\boldsymbol{x},t) - \frac{\Delta t}{\tau}\left[f_i(\boldsymbol{x},t) - f_i^{\mathrm{eq}}(\boldsymbol{x},t)\right]$$

Streaming : $$f_i(\boldsymbol{x} + \boldsymbol{c}_i\Delta t, t + \Delta t) = f_i^\star(\boldsymbol{x},t)$$

Relation between mesoscopic and macroscopic variables : $$\rho(\boldsymbol{x},t) = \sum_i f_i(\boldsymbol{x},t) \qquad \rho\boldsymbol{u}(\boldsymbol{x},t) = \sum_i \boldsymbol{c} f_i(\boldsymbol{x},t)$$

- How is Lattice Boltzmann Methods different from Navier Stokes?
  *“Non-linearity is local and Non-locality is linear”**

*attributed to Dr. Sauro Succi

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Graphical Processing Unit (GPU)

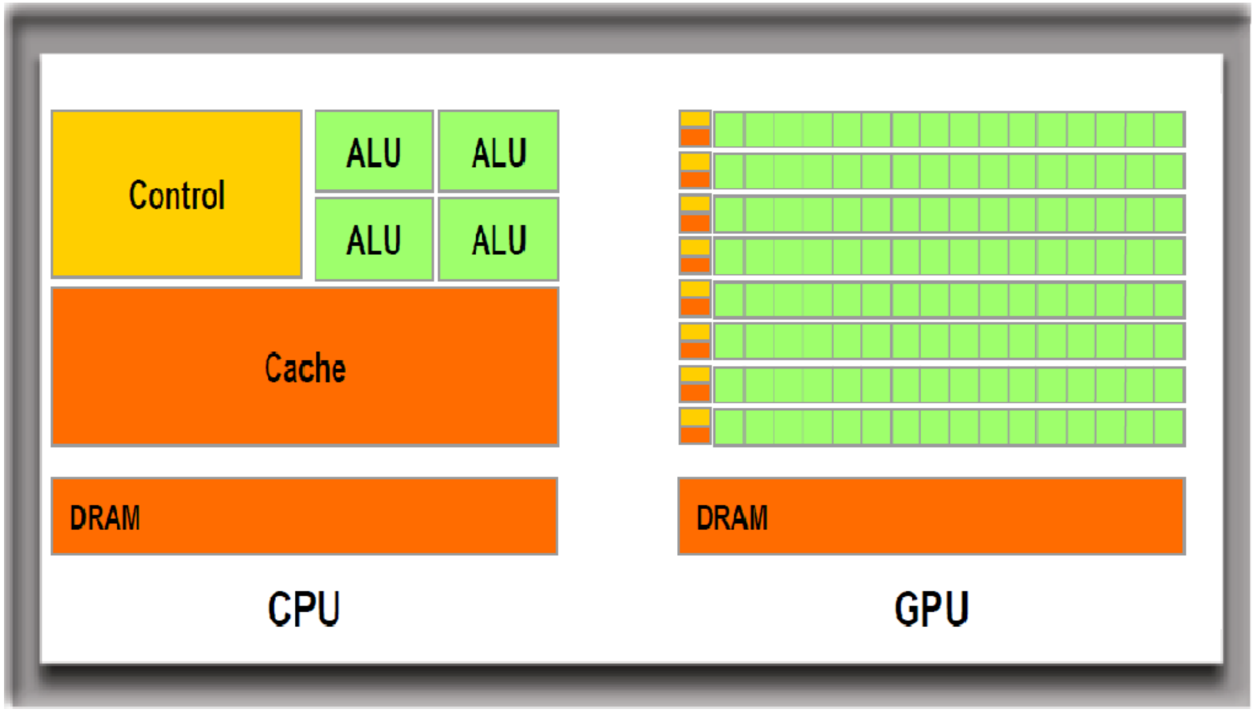
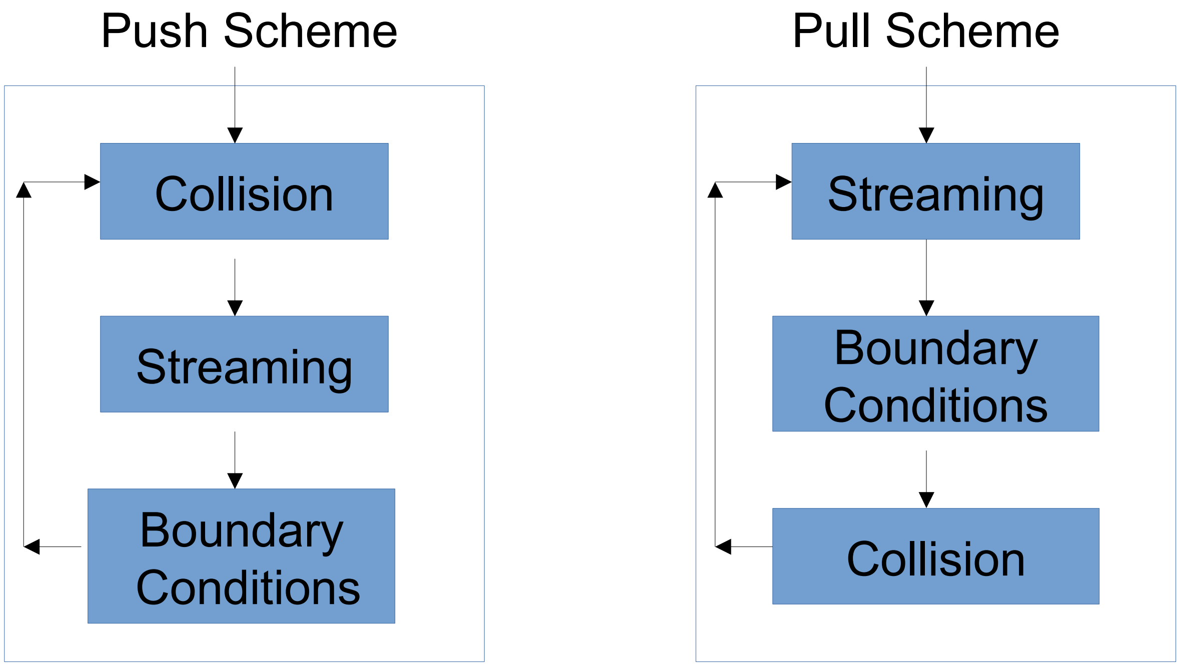


Image credit : http://www.keremcaliskan.com/wp-content/uploads/2011/01/CPU-GPU-Structures1.png

Lattice Boltzmann Methods in GPUs



- Push scheme is easier to combine collision and streaming
- Pull scheme helps to avoid uncoalesced writing

$$f_i^{\star}(\boldsymbol{x},t) = f_i(\boldsymbol{x},t) - \frac{\Delta t}{\tau}\left[f_i(\boldsymbol{x},t) - f_i^{\mathrm{eq}}(\boldsymbol{x},t)\right]$$

Collision

$$f_i(\boldsymbol{x} + \boldsymbol{c}_i\Delta t, t + \Delta t) = f_i^{\star}(\boldsymbol{x},t)$$

Streaming

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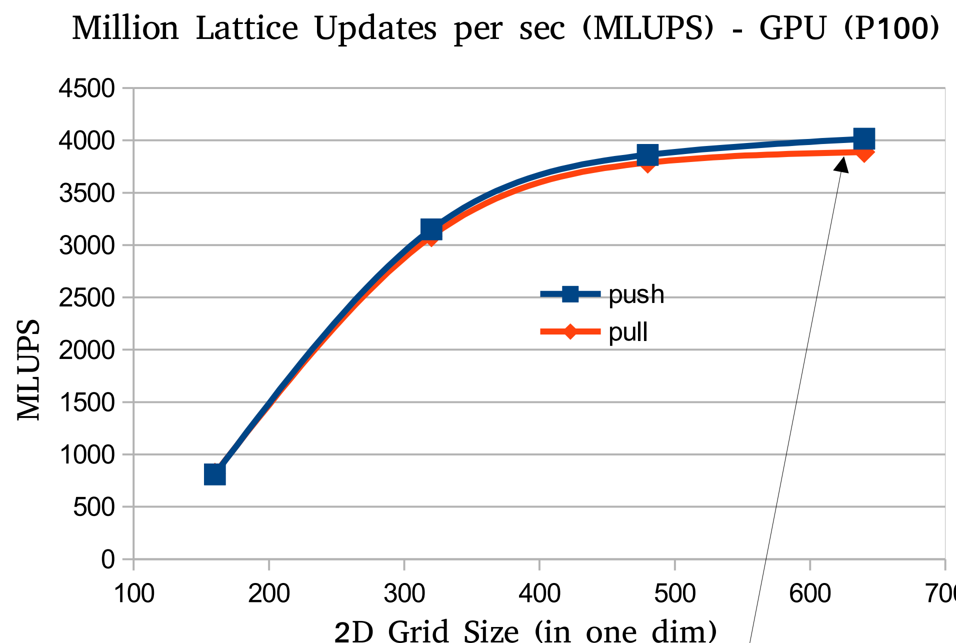
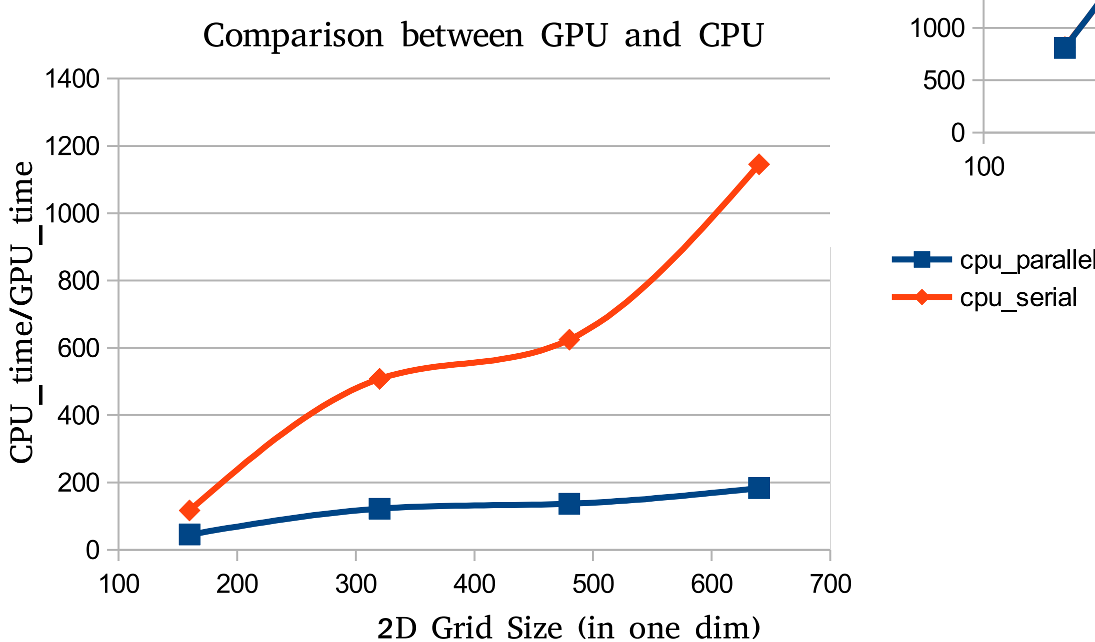
Graphical Processing Unit (GPU)

CPU :
Intel Xeon E5-2680 v4 (Broadwell, 14 cores/28 threads, 2.40GHz) processors, 128GB memory

GPU :
NVIDIA Tesla P100 (Pascal) GPUs -- 5.3TF peak (double precision), 16GB memory





Higher than any MLUPS published using single GPU for 2D Lid Driven Cavity

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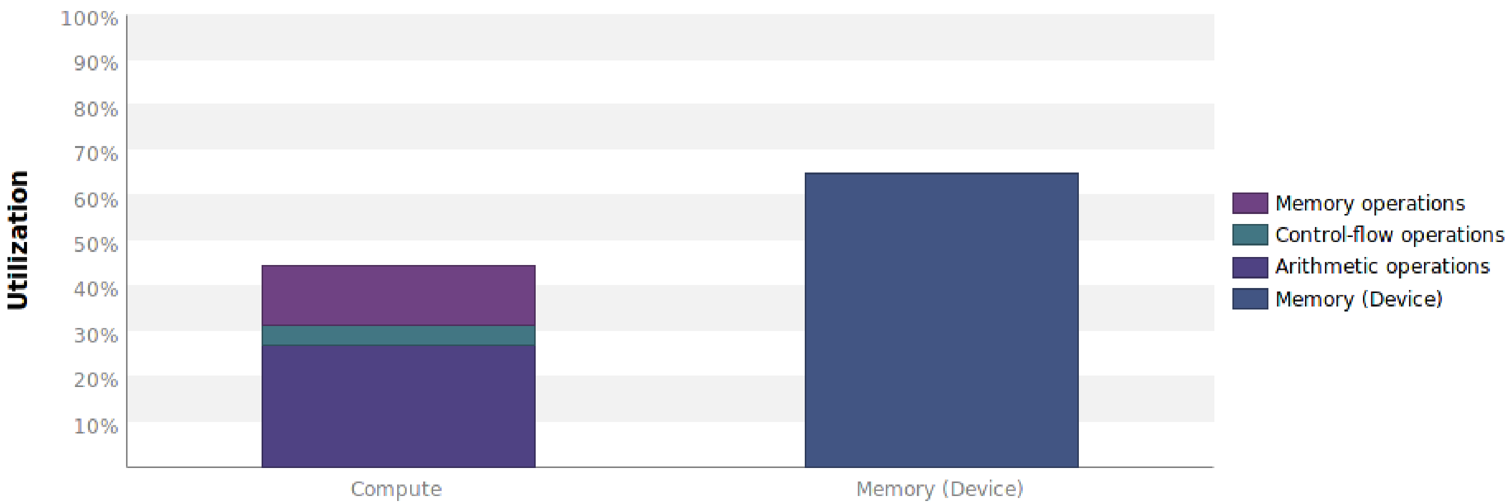
Graphical Processing Unit (GPU)

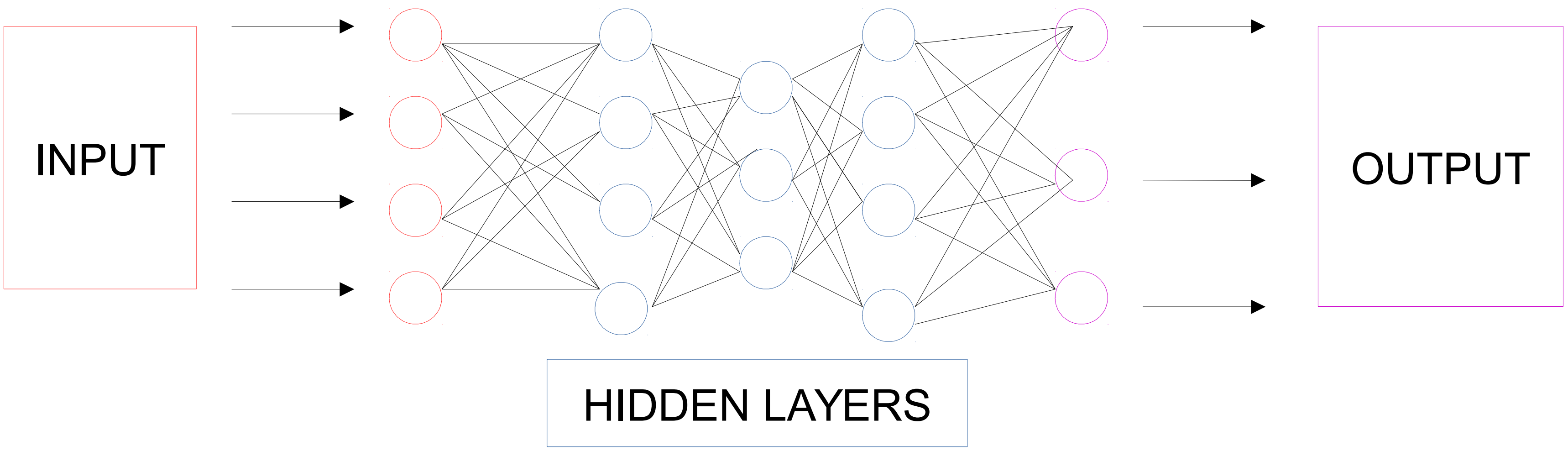
Performance Analysis :

- Theoretical occupancy : 50%, Achieved occupancy : 48%
- Divergence : 5% , Warp Execution efficiency : 99.6%
- Global memory load efficiency : 48%



Machine Learning

What is Neural Network



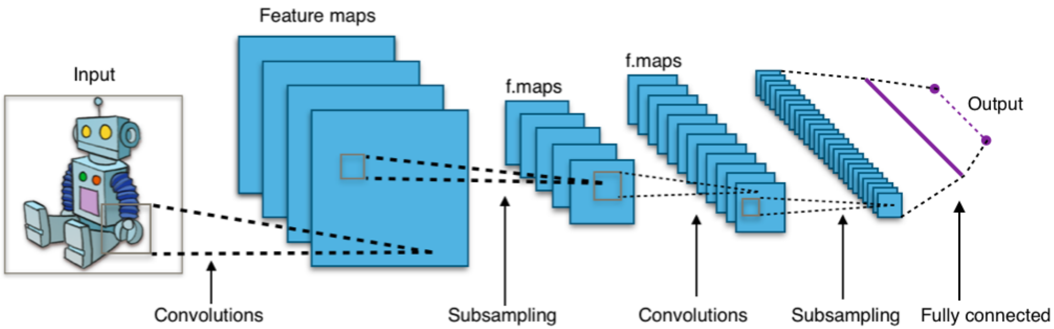
Self Driving Cars

Natural Language Processing

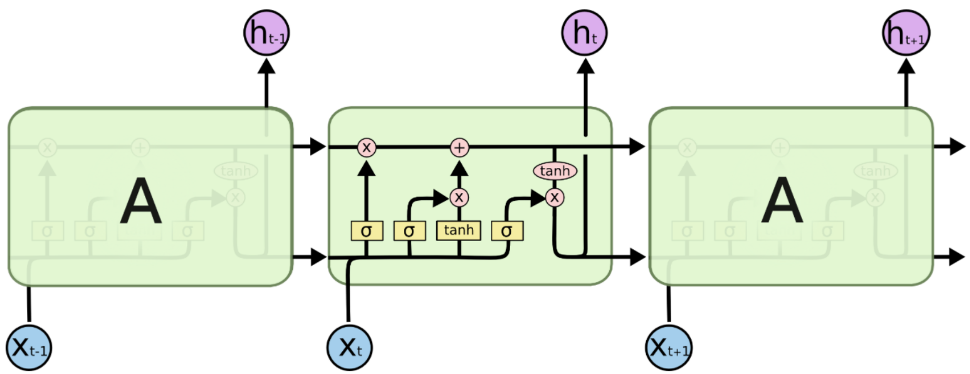
Product Sales

Machine Learning

Neural Networks



Convolutional Neural Networks (CNN) , Wikipedia

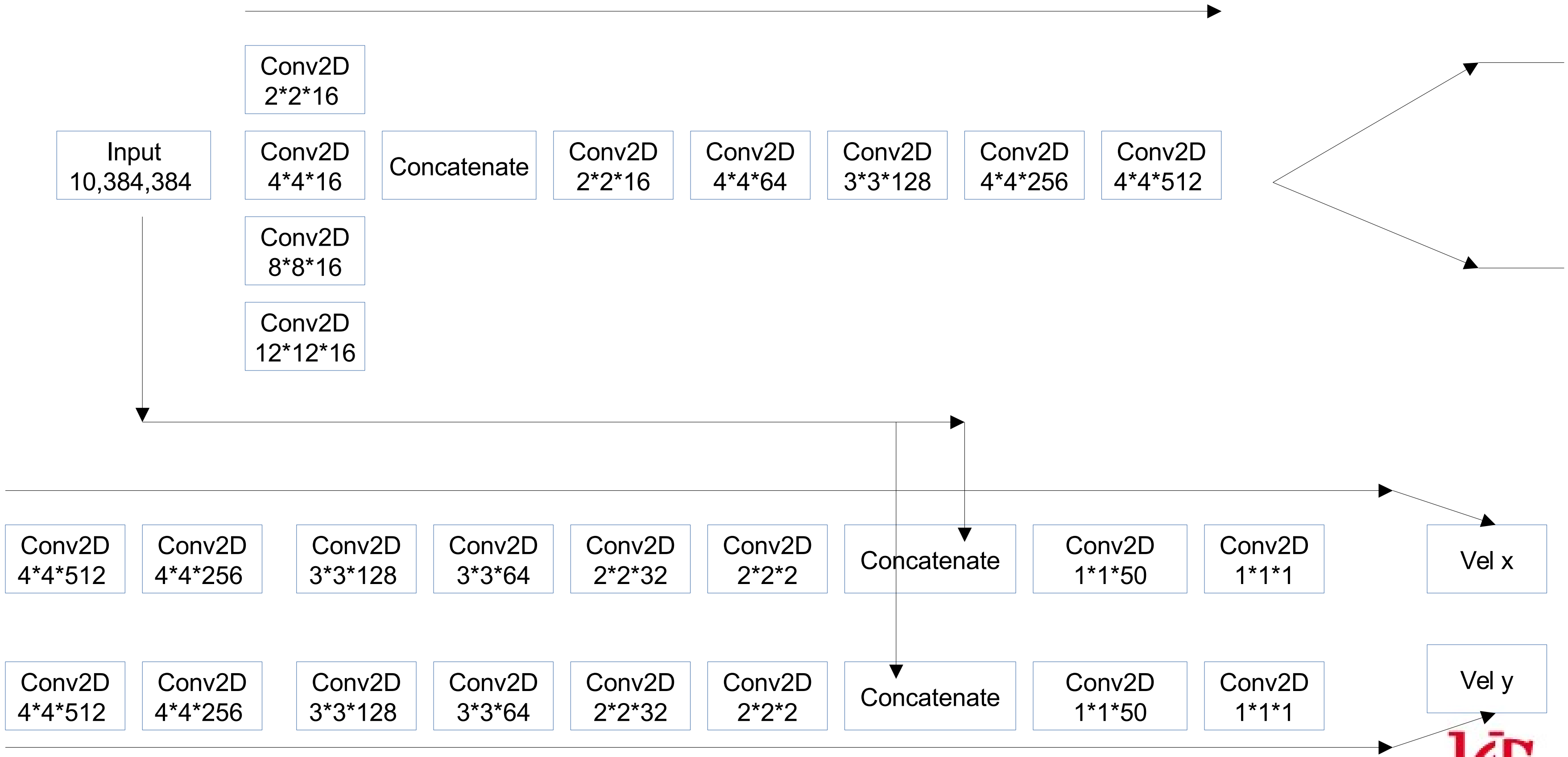


The repeating module in an LSTM contains four interacting layers.

Long Short Term Memory, type of Recursive Neural Network, © Christopher Olah

Machine Learning

CNN architecture for 2D Lid Driven Cavity data



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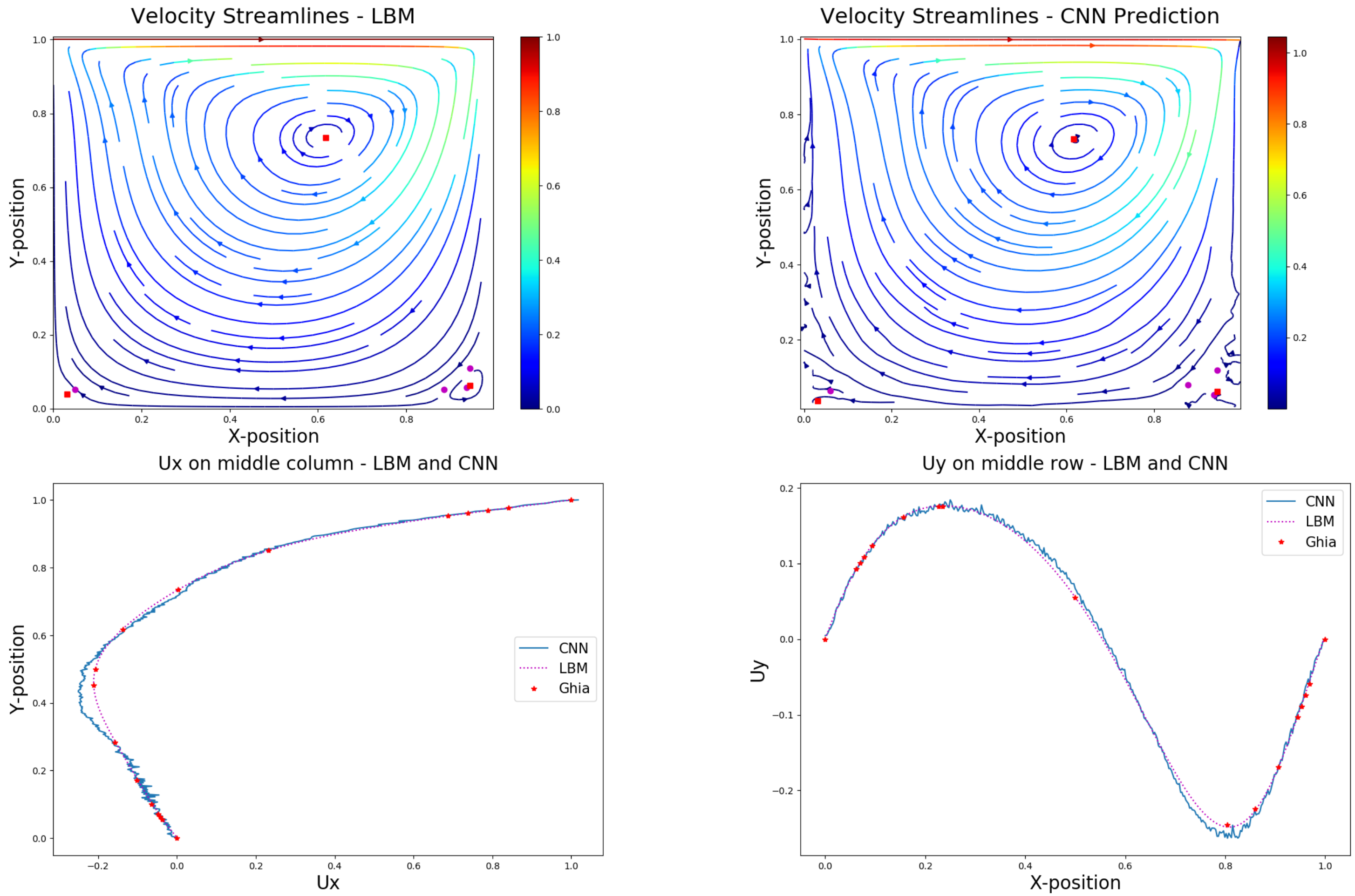
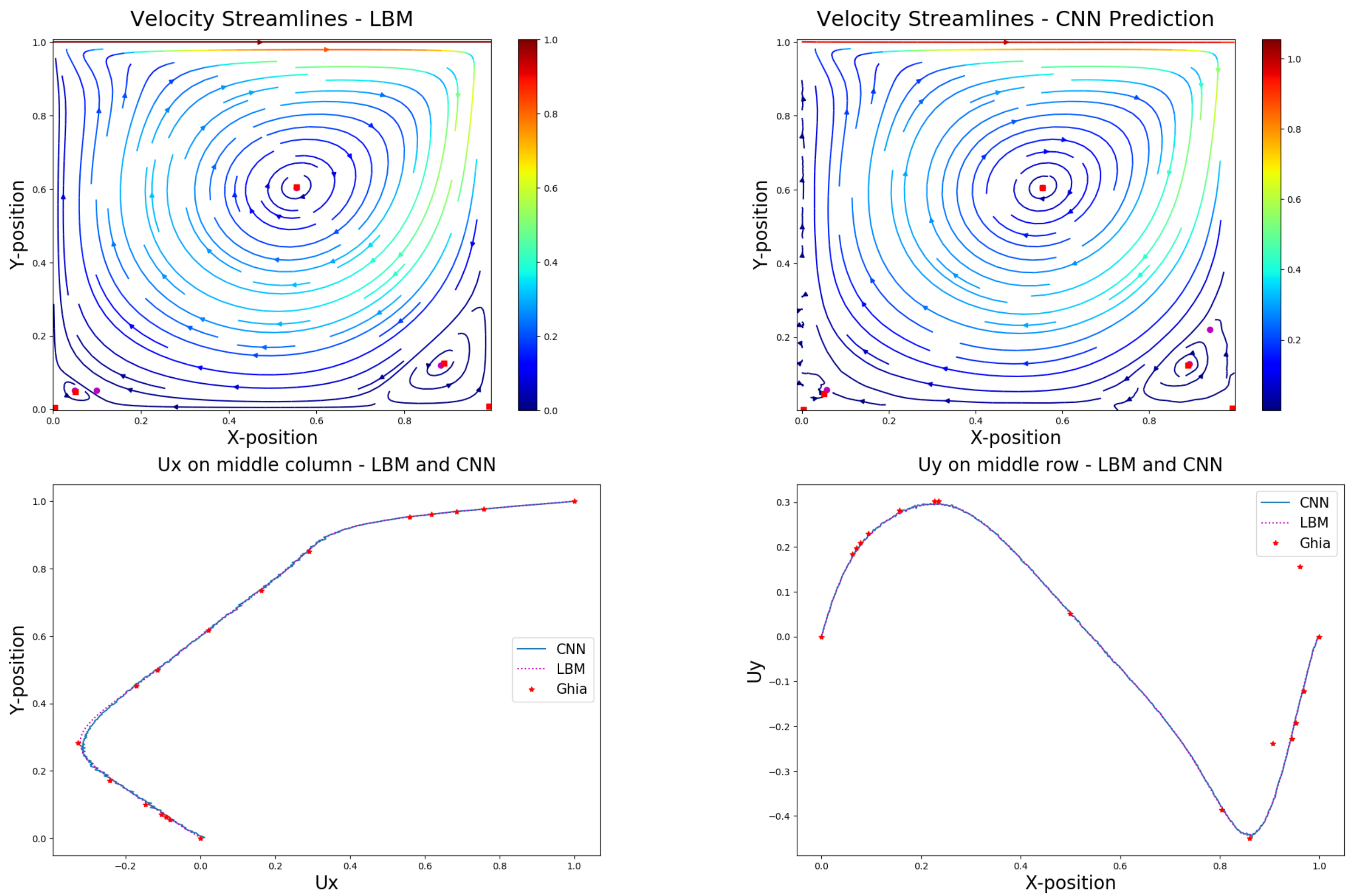
CNN Results - Re100

Comparison of LBM and CNN Prediction for LDC at Re 100 for grid size of 384*384



CNN Results - Re400

Comparison of LBM and CNN Prediction for LDC at Re 400 for grid size of 384*384



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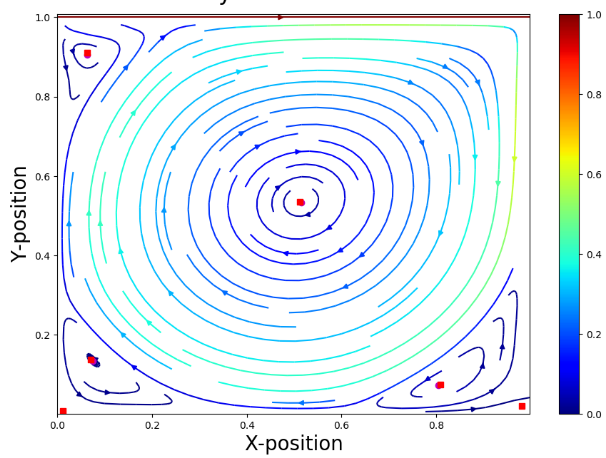
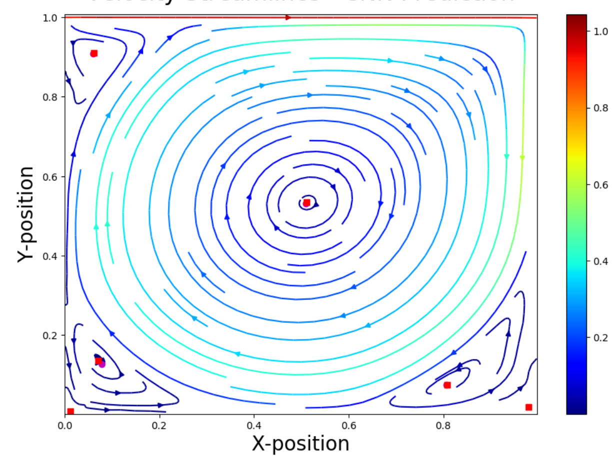
CNN Results - Re5000

Comparison of LBM and CNN Prediction for LDC at Re 5000 for grid size of 384*384

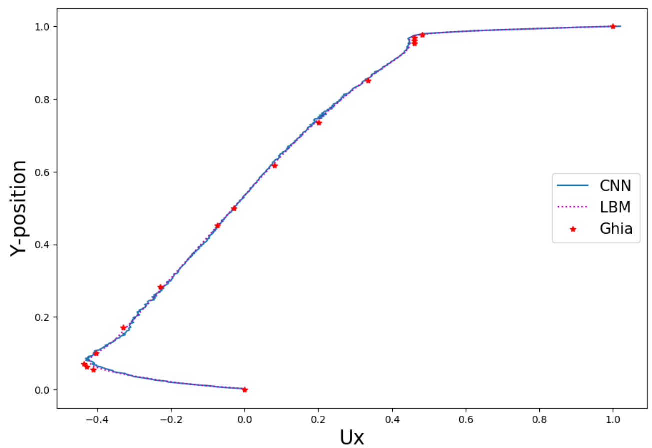
Velocity Streamlines - LBM



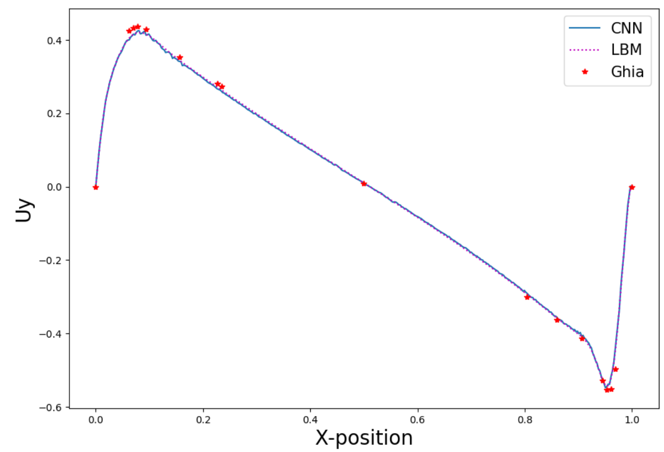
Velocity Streamlines - CNN Prediction



Ux on middle column - LBM and CNN



Uy on middle row - LBM and CNN



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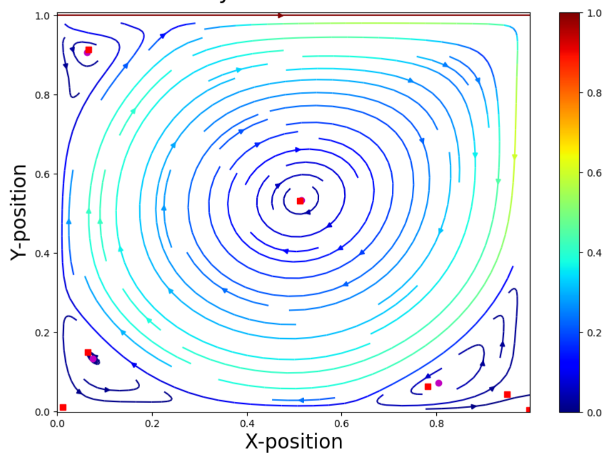
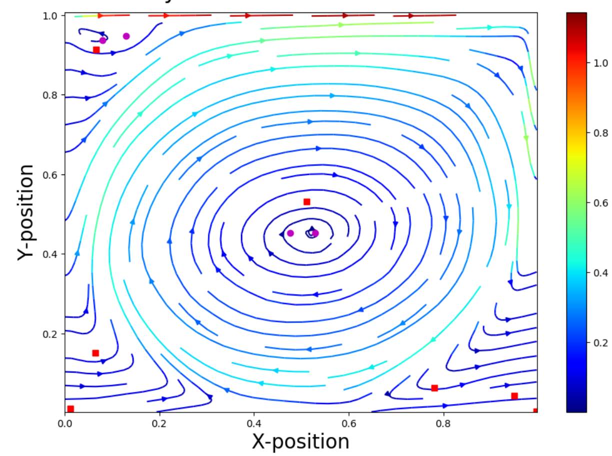
CNN Results - Re7500

Comparison of LBM and CNN Prediction for LDC at Re 7500 for grid size of 384*384

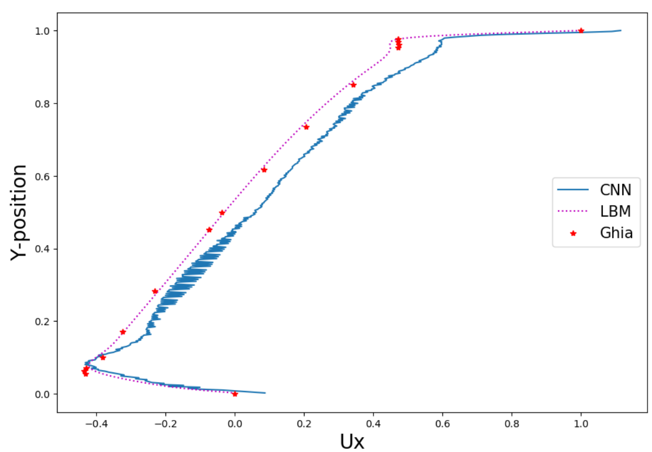
Velocity Streamlines - LBM



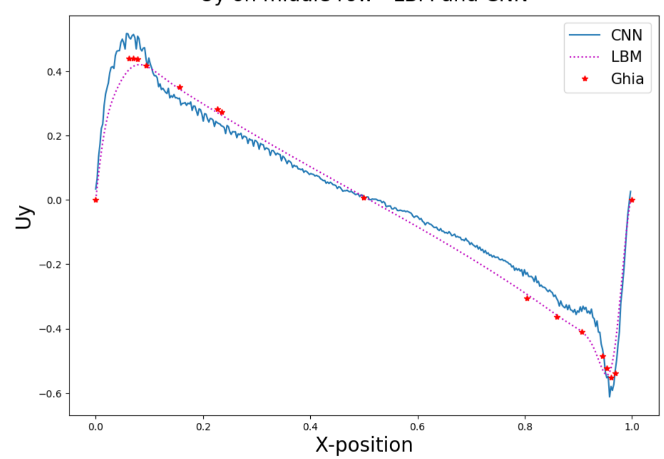
Velocity Streamlines - CNN Prediction



Ux on middle column - LBM and CNN



Uy on middle row - LBM and CNN



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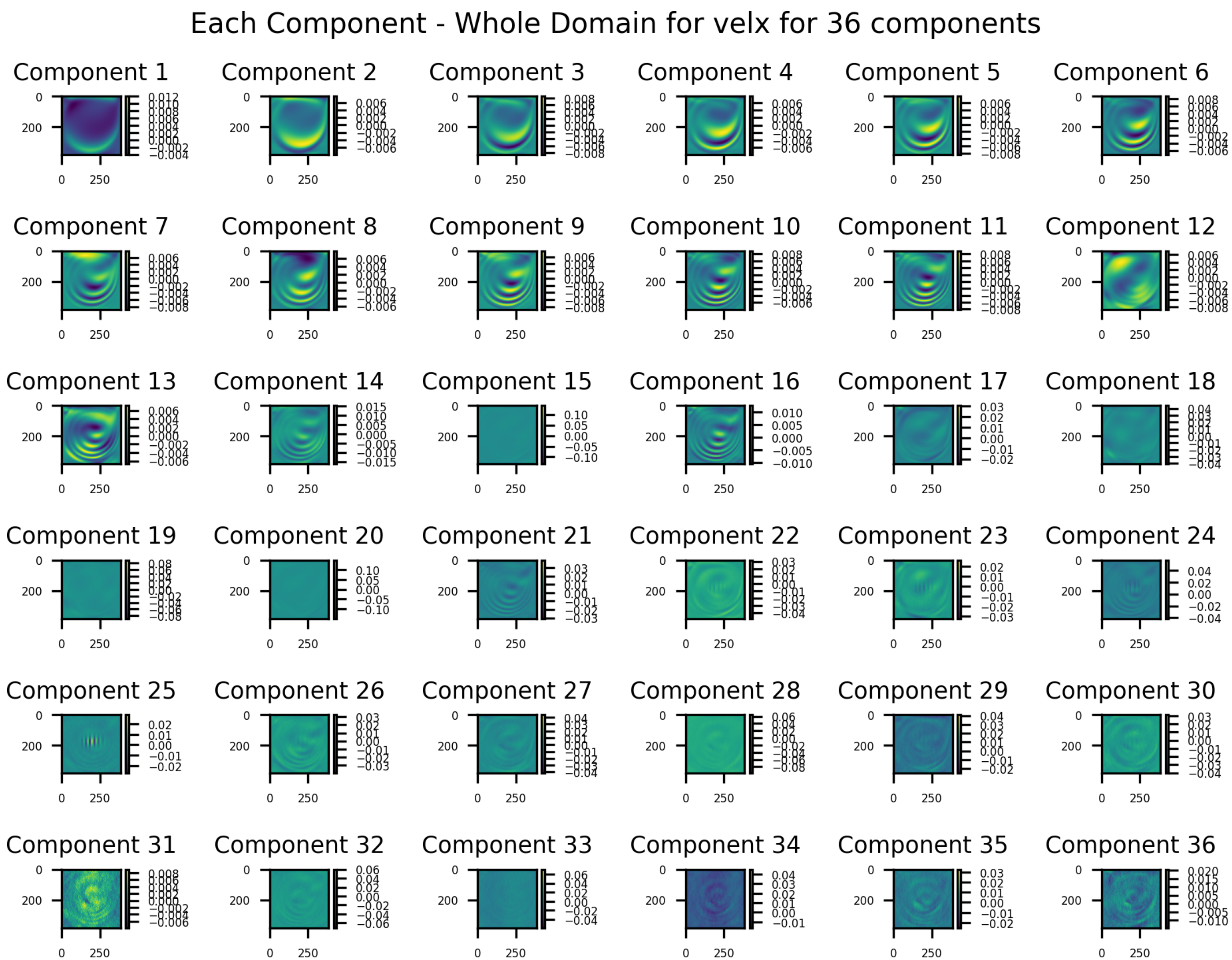
Machine Learning

How about Recursive Neural Networks ?

- Need more data
- Need more computational power

What if we reduce the dimensionality of data?

PRINCIPAL COMPONENT ANALYSIS – Velx



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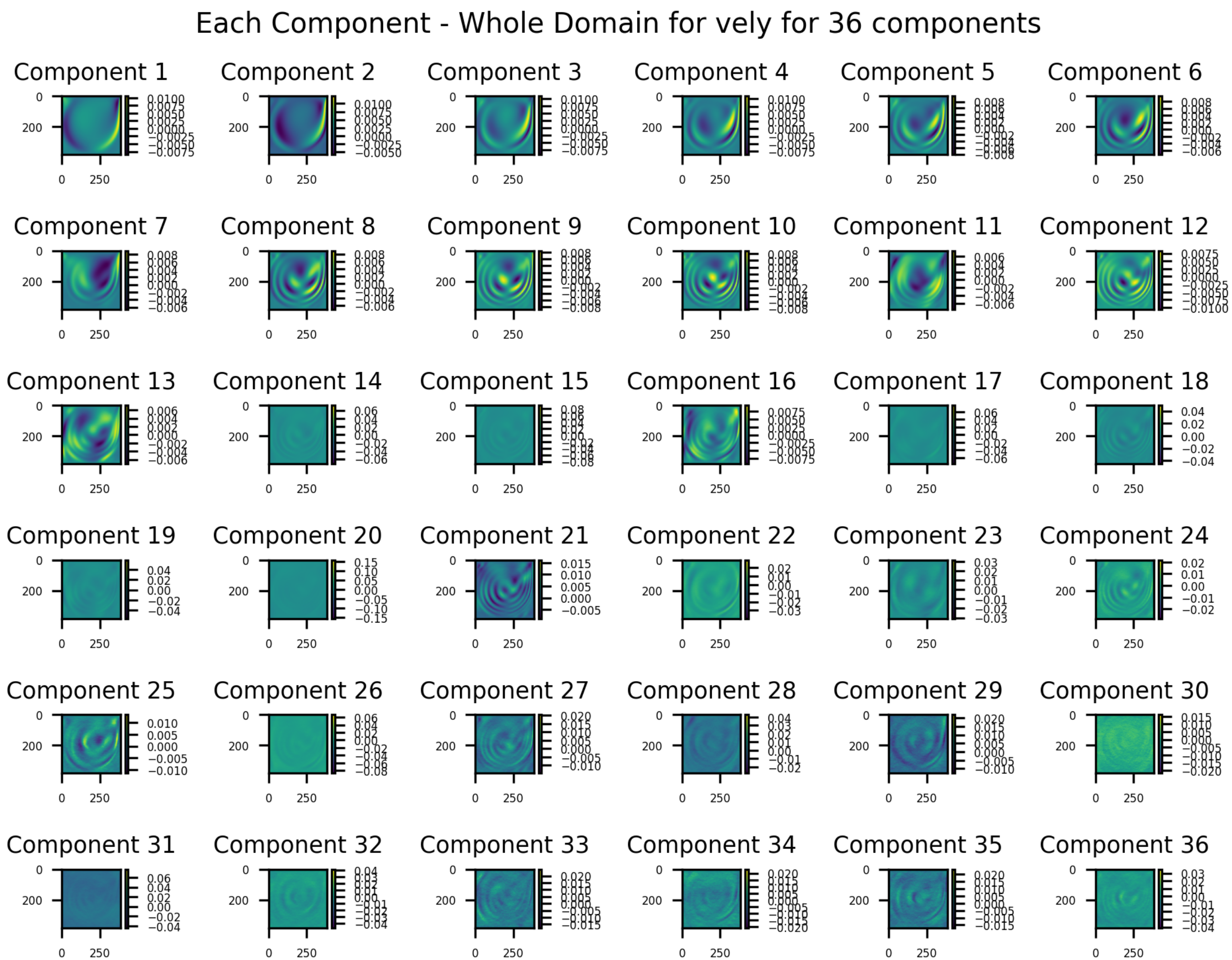
PRINCIPAL COMPONENT ANALYSIS – Vely



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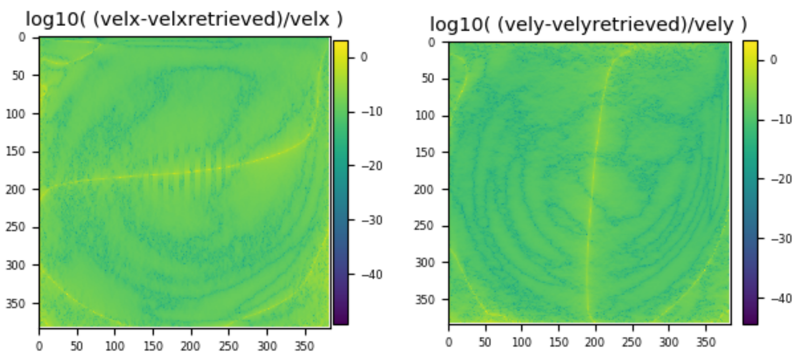
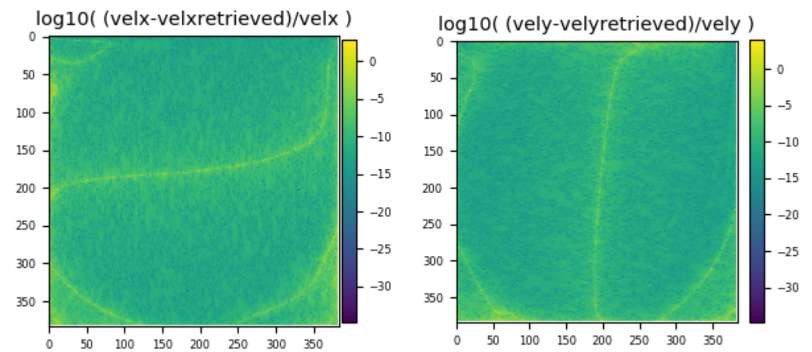
PRINCIPAL COMPONENT ANALYSIS

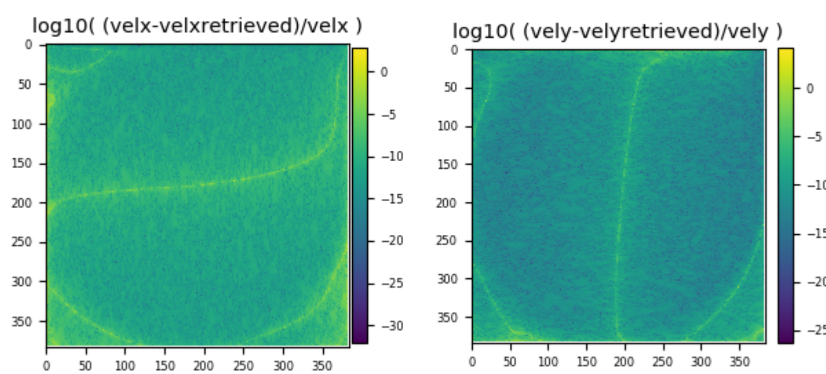
Difference between vel and vel retrieved at Re5000 for 16 components



Difference between vel and vel retrieved at Re5000 for 25 components



Difference between vel and vel retrieved at Re5000 for 36 components



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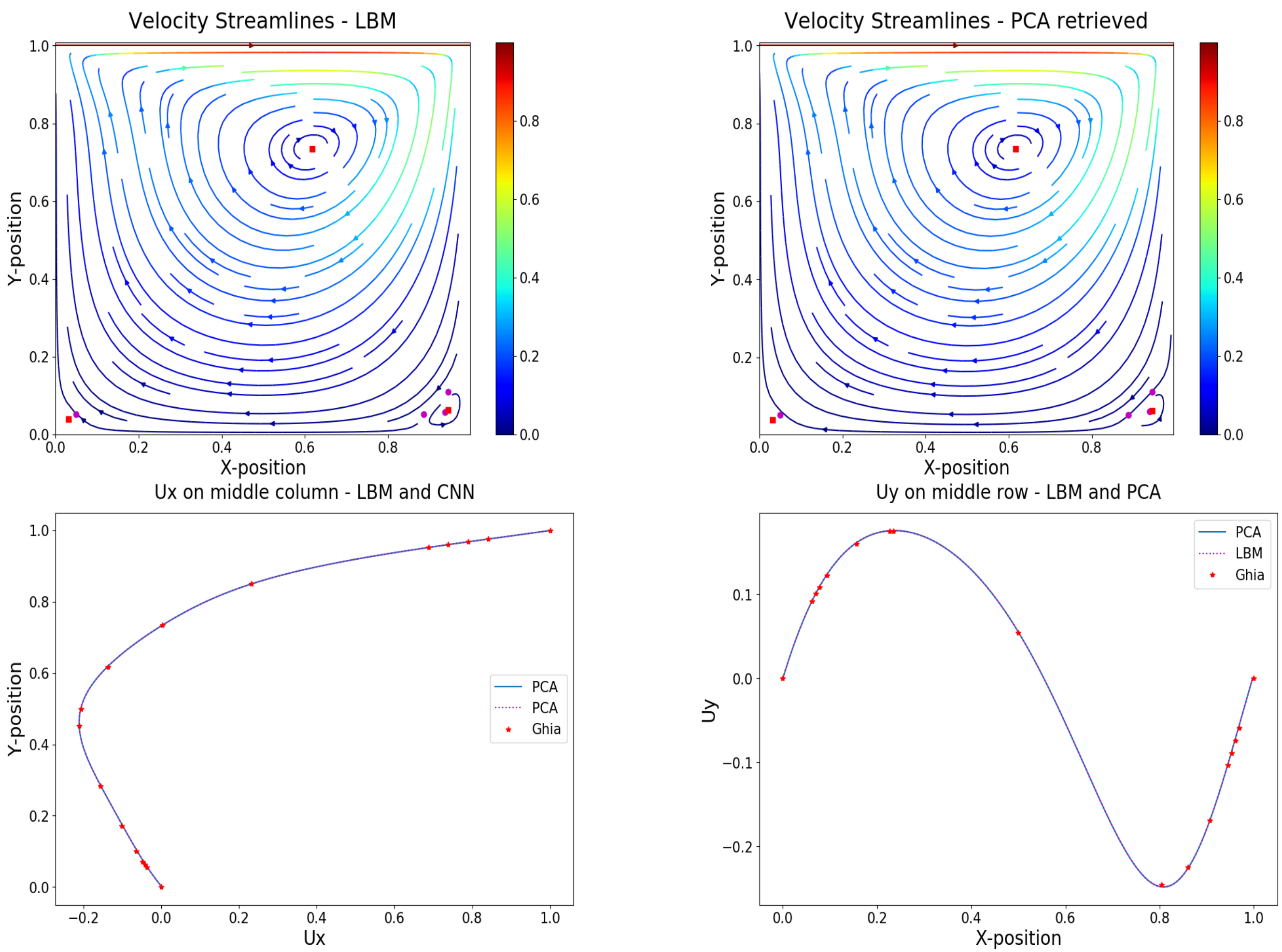
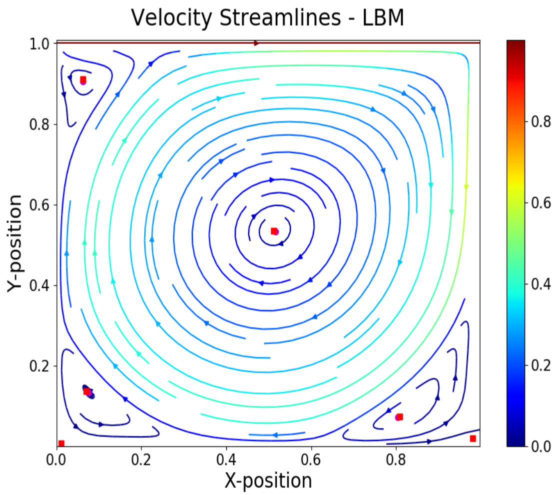
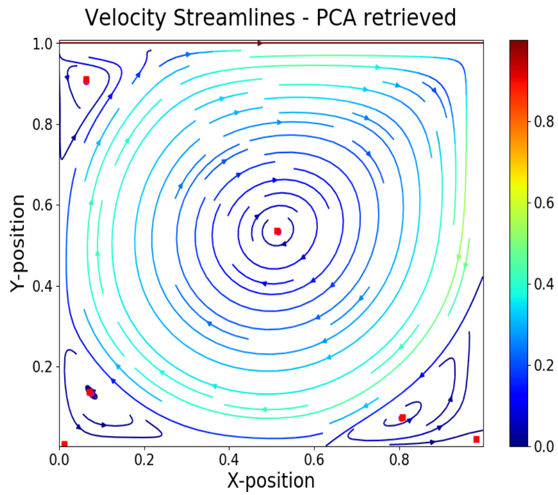
Comparison of LBM and PCA retrieved for LDC at Re 100 for grid size of 384*384 for 36 components

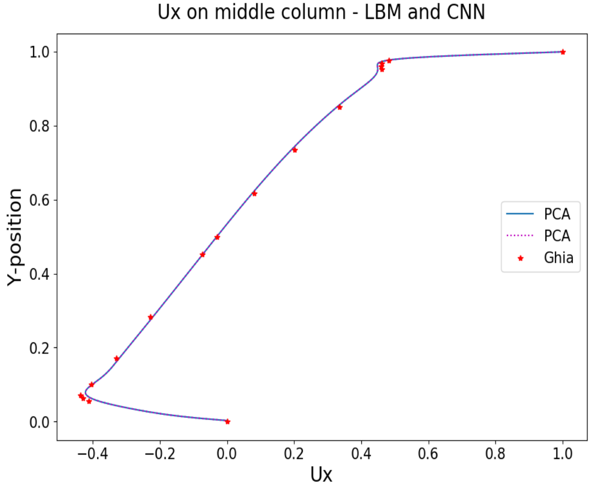


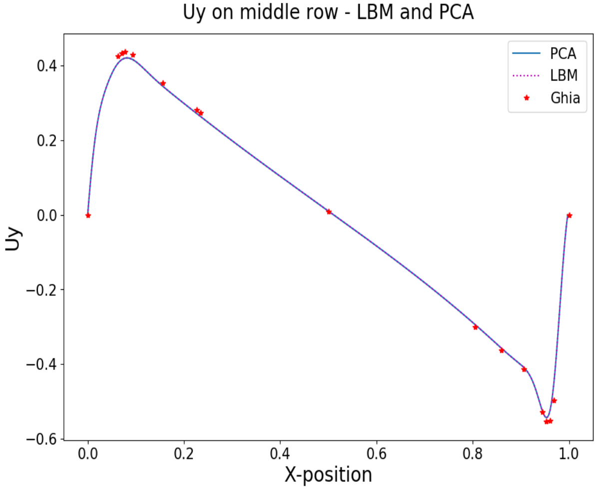
Machine Learning

Comparison of LBM and PCA retrieved for LDC at Re 5000 for grid size of 384*384 for 36 components

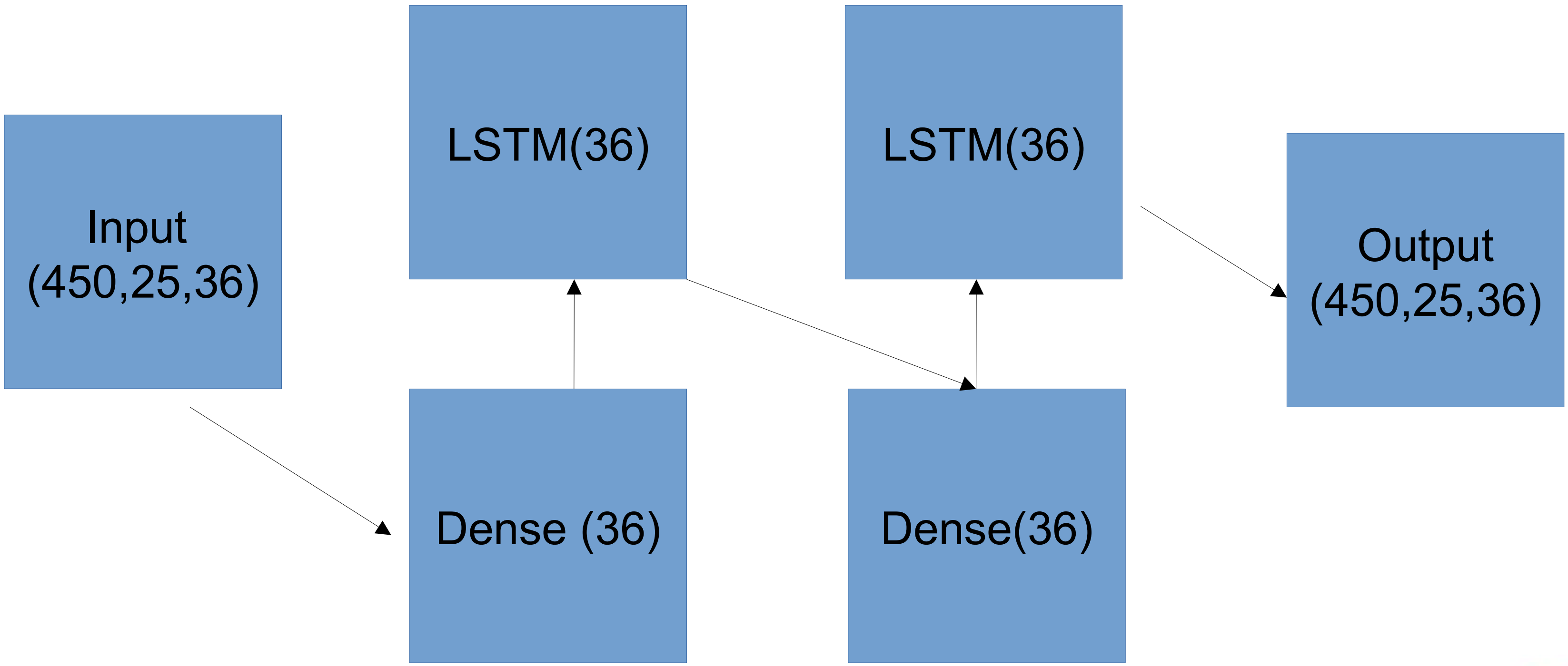




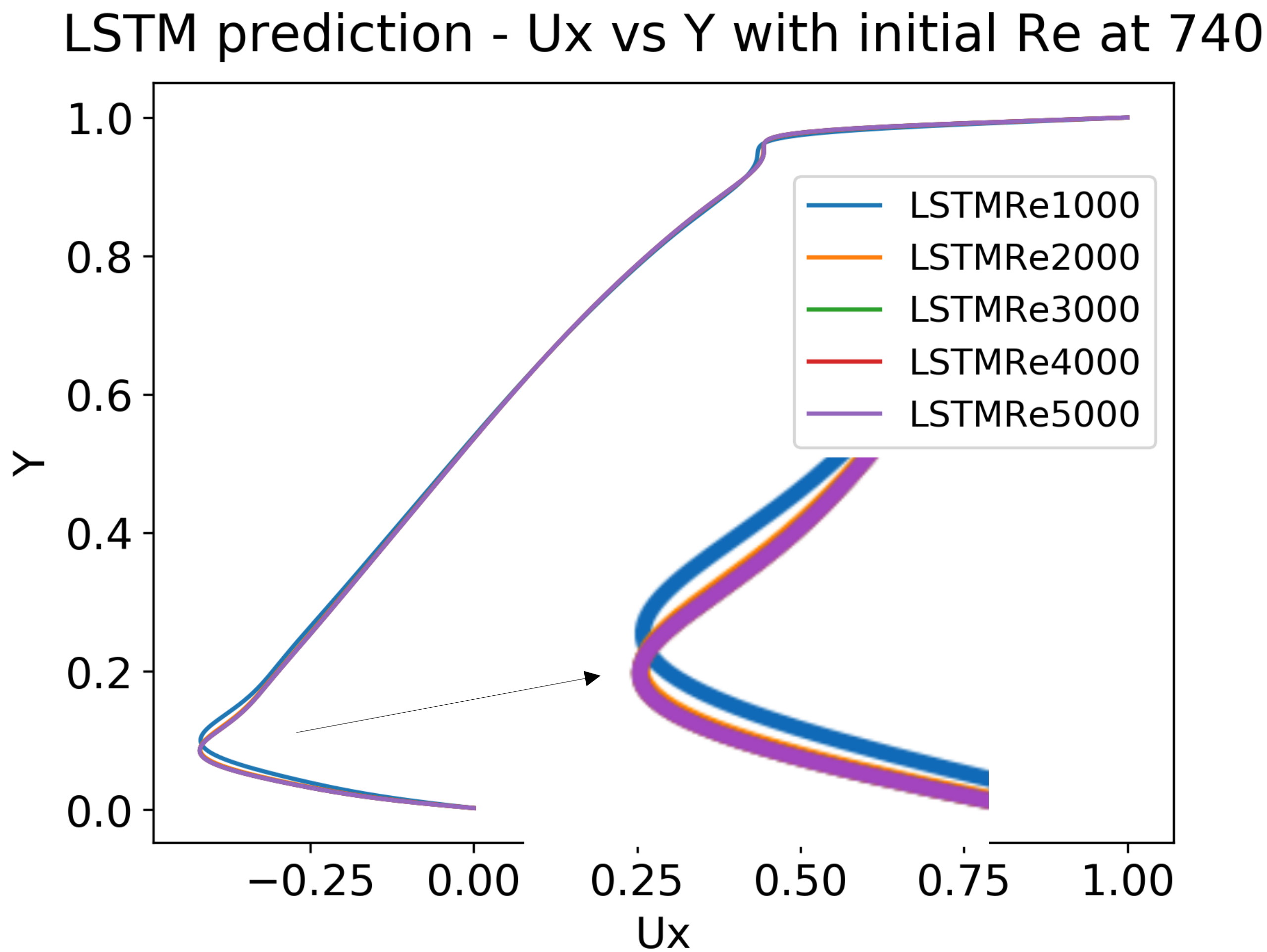




LSTM architecture



Machine Learning



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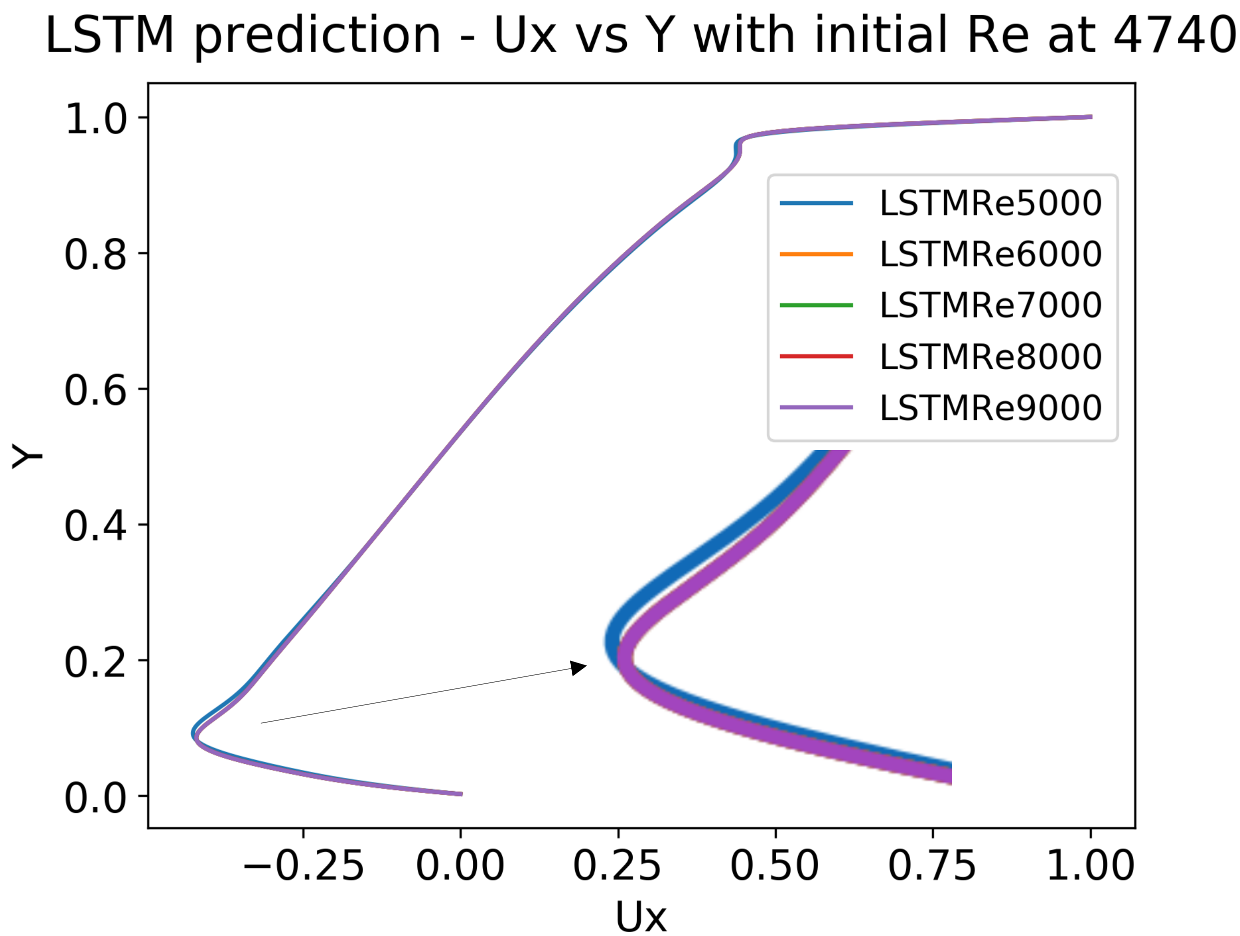

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Conclusion

- GPU speedup is multiple orders of magnitude and has more room to improve.
- Machine Learning , in its current status, is too demanding to play a part yet in high fidelity fluid flow simulations*.

***Recommended read** : *Accelerating Eulerian Fluid Simulation With Convolutional Networks*. Jonathan Tompson, Kristofer Schlachter, Pablo Sprechmann, Ken Perlin. 2016..

Thank you

Questions ?