Speeding up wave propagation modeling
Final

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Introduction & Problem statement

We have

$$u_{tt}(t,x,z) - v^2(x,z)\Delta u(t,x,z) = q(t)\delta(x - x_s, z - z_s)$$

and finite difference method as the solution.

Aim:

- To speed up acoustic equation solution using using neural networks.

Input:

- time and space discretizations Δt, $\Delta x = \Delta z$
- impulse source time-series $q(t_i)$ and location x_s, z_s.
- special velocities $v(x,z)$ at data points

Full convolutional architecture as shapes vary

Data generation: velocity modeling

- Geo-realistic Marmousi-II model [1].
- Texture transferring using Random Gaussian field context [1].

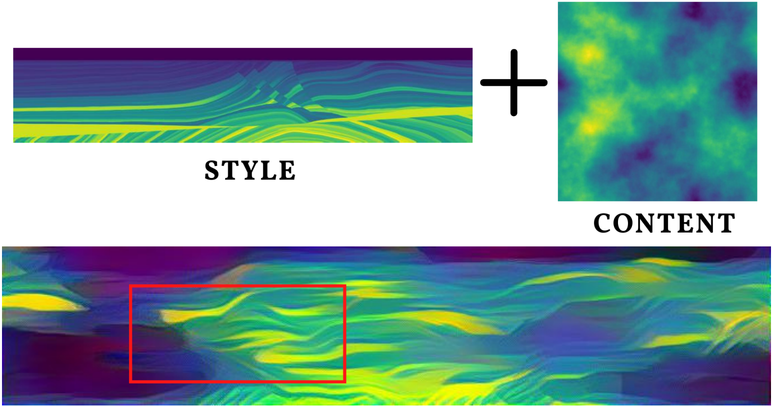


Figure: NST - style: Marmousi model, content: Gaussian field

Data generation

Generation:

- Velocity models generation $v(x, z)$:
- Ricker source $\left(A \cdot \left(1 - 2(\pi f_0 x)^2\right) \cdot exp\left(-(\pi f_0 x)^2\right)\right)$ with varying frequency f_0 under the condition

$$\begin{cases} f_0 & \in [6,\ 256] \\ \Delta x \cdot & \leq \frac{\min\{|v|\}}{N_\lambda f_{\max}} \end{cases}$$

  where $f_{\max} = 2.5 f_0$
- CFL condition:

$$\Delta t \leq \frac{\Delta x}{\sqrt{2} \max\{|v|\}}$$

- Random source locations strictly in the interior

Model:

Quality:

- Correlation coefficient between normalized wavefields.
- Execution time.

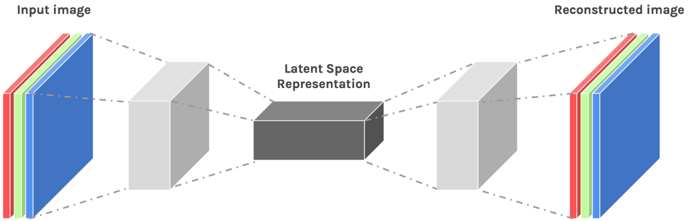
Normalization is equivalent to the source change:

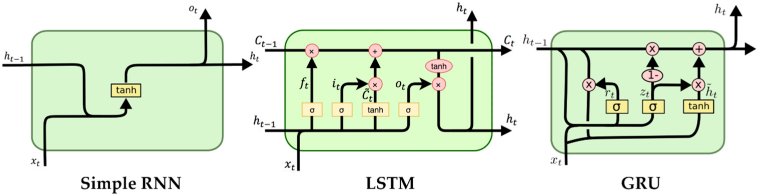
$$u \to Cu, \quad q \to Cq\frac{\Delta t^2}{\Delta x^2} \quad v \to v\frac{\Delta t}{\Delta x}$$

$$u_{t+1} = 2u_t - u_{t-1} + v^2\Delta t^2\Delta^{(h)}u_t + q_t\frac{\Delta t^2}{\Delta x^2}\delta(x-x_s, z-z_s)$$

$$u_{t+1} = \begin{bmatrix} v^2\Delta t^2\Delta^{(h)}+2 & -1 \end{bmatrix}\begin{bmatrix} u_t \\ u_{t-1} \end{bmatrix} + q_t\frac{\Delta t^2}{\Delta x^2}\delta(x-x_s, z-z_s)$$

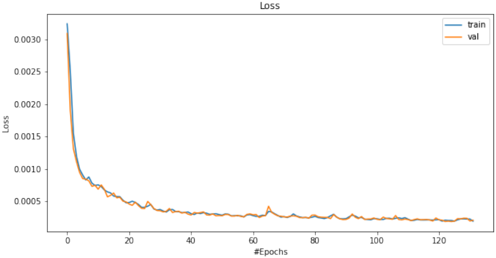
Model:

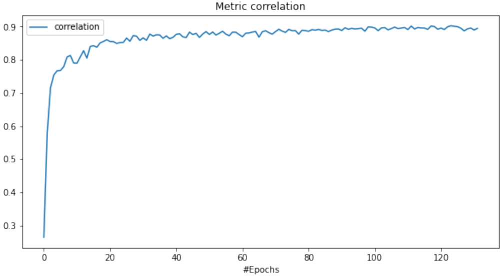




Weights pruning: $\mathrm{ReLU}(|W| - f(s))$

Results:





$n_x = n_z = 240$

$n_t = 40$

prooning $\approx 65\%$

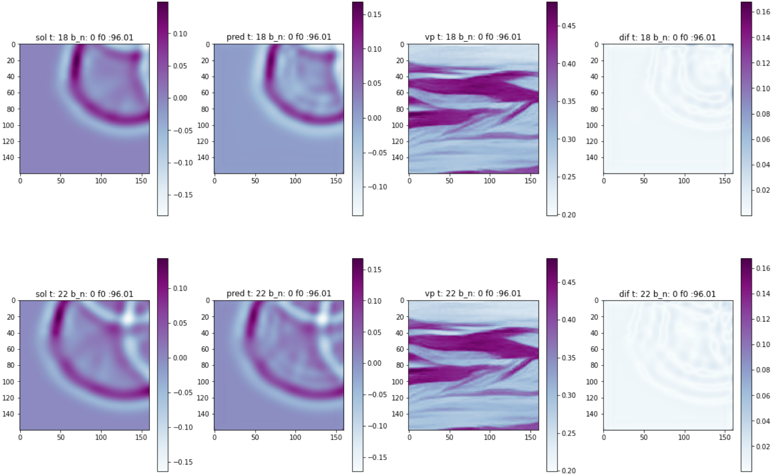
$t_{pred} \approx 0.7 sec$

$t_{dm} \approx 1.2 sec$

$corr \approx 0.93$

$\Delta T = 10 \Delta t$

Results:



Example: ref_1 ref_2 ref_3

Discussion:

- We are not restricted with CFL
- Considered only impulse source
- Error accumulation
- Still need FD at the beginning
- Sparse convolutional nets should be implemented
- Extend solution to avoid both CFL and Nyquist conditions
- Extend to the case of arbitrary time prediction
- Implement physics informed loss

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Thank you!
Questions?