Speeding up wave propagation modeling
CheckPoint # 3

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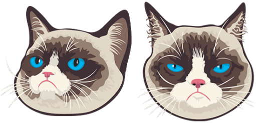


Introduction & Problem statement

Aim:

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

Input:

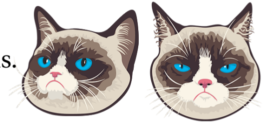
- time and space discretizations Δt, $\Delta x = \Delta z$
- time and space pints amout n_t, n_x, n_z
- impulse source time-series $q(t_i)$ and location x_s, z_s.
- special velocities $vp(x, z)$ at data points
- absorbing boundary conditions

Output:

- The solution of acoustic equation $u(x, z, t)$ at some point of time t.

Quality:

- RMSE error between normalized wavefields $\frac{u(x,z,t)}{\sigma(u)}$.
- Correlation coefficient between normalized wavefields.
- Execution time.



Data generation: velocity modeling

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

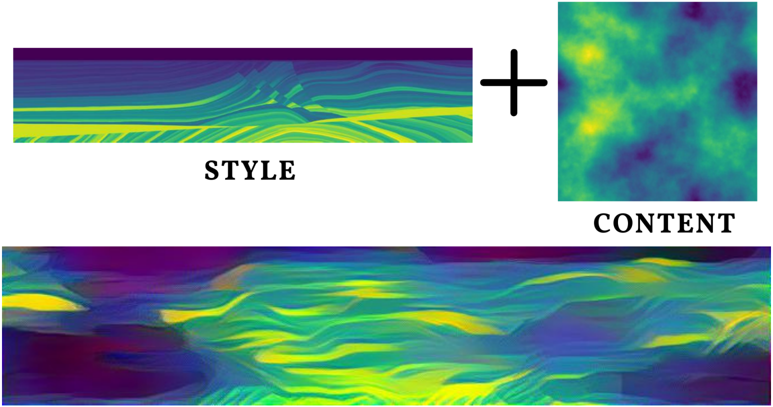


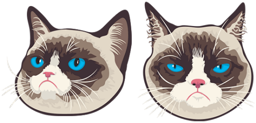
Figure: NST - style: Marmousi model, content: Gaussian field

Data generation: velocity modeling

- Geo-realistic scaling.

$$\left.\begin{aligned} &1)\ \mathrm{vp} = \mathrm{vp} - \mathrm{vp.min()} \\ &2)\ \mathrm{vp} = \frac{\mathrm{vp}}{\mathrm{vp.max()}} \end{aligned}\right\} \text{transform to scale } [0, 1]$$

$$\left.\begin{aligned} &[\mathrm{low},\ \mathrm{high}] \in [500, 10000] \\ &3)\ \mathrm{vp} = \mathrm{vp} * (\mathrm{high} - \mathrm{low}) + \mathrm{low} \end{aligned}\right\} \text{transform to scale } [\mathrm{low},\ \mathrm{high}]$$



Data generation

Generation:

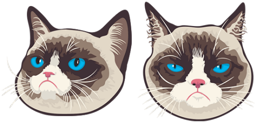
- Velocity models generation $vp(x,z)$:
- Nyquist frequency varying N_λ
- Space discretization varying $\Delta d,\ \Delta z = \Delta x = \Delta d$
- Ricker source with varying frequency f_0 under the condition

$$\begin{cases} f_0 & \in [6,\ 256] \\ \Delta x \cdot & \le \dfrac{\text{vp.min()}}{N_\lambda f_{\max}} \end{cases}$$

- Discretizations to fulfill CFL condition:

$$\Delta t \le \frac{\Delta x}{\sqrt{2}|vp(x,z)|.\max()}$$

- Random source locations



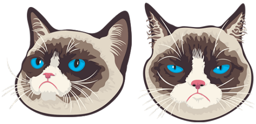
Model:

In the previous series

- Convolutional Auto-Encoder + L1Loss/MSE
- Convolutional Auto-Encoder + GRU Cell at the bottleneck + L1Loss/MSE
- UNet (UNet++)[8] + L1Loss/MSE
- Fully-Connected + Physic's Informed Loss [5]
- Convolutional + Physic's Informed Loss

Time is precious

- Avoid skip connections to reduce convolutions on large images
- Avoid point-wise prediction using FC layers
- Avoid extra encoder-decoder passes
  to predict full sequence



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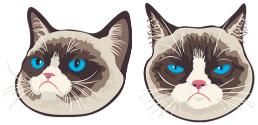

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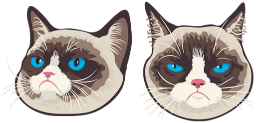

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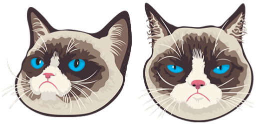


Model:

But still let us use Auto-Encoder as base-line

- Convolutional Auto-Encoder + L1Loss/MSE

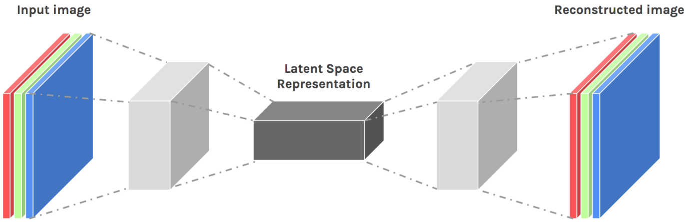
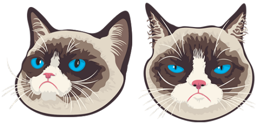


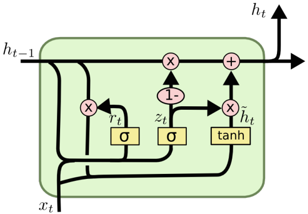
Figure: Convolutional Auto-Encoder

Input image: $u(x,z,t_i) + \frac{q(t_i)\Delta x^2}{\Delta t^2} \cdot \delta(x - x_s, z - z_s),\ vp(x,z)$



Model:

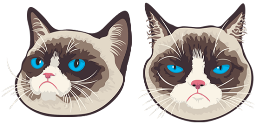
- Convolutional Auto-Encoder + GRU Cell at the bottleneck + L1Loss/MSE



$$z_t = \sigma(W_{hz} * h_{t-1} + W_{xz} * x_t + b_z)$$
$$r_t = \sigma(W_{hr} * h_{t-1} + W_{xr} * x_t + b_r)$$
$$\hat{h}_t = \Phi(W_h * (r_t \odot h_{t-1}) + W_x * x_t + b)$$
$$h_t = (1 - z_t) \odot h_{t-1} + z \odot \hat{h}_t$$

Figure: Convolutional GRU Cell [7]

Input image: $u(x, z, t_i) + \frac{q(t_i)\Delta x^2}{\Delta t^2} \cdot \delta(x - x_s, z - z_s)$
Hidden initial image: $vp(x, z)$



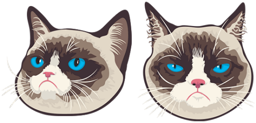
Model: Can we do faster?

In the sequential convolutions some weights could be too small to provide some influence on predictions

Thought-full weights thresholding

$$\widehat{W} = \text{ReLU}(W - f(s))$$

where s is a new trainable parameter and $f(\cdot)$ some nonlinearity [2]



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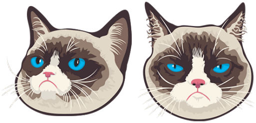
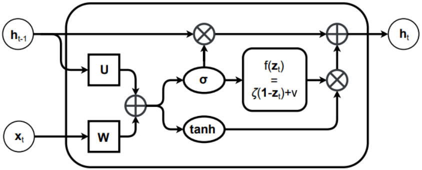


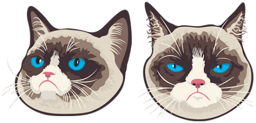
Model: Can we do faster?

Reduce GRU inner complexity



$$\mathbf{z}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_z),$$
$$\tilde{\mathbf{h}}_t = \tanh(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_h),$$
$$\mathbf{h}_t = (\zeta(\mathbf{1} - \mathbf{z}_t) + \nu) \odot \tilde{\mathbf{h}}_t + \mathbf{z}_t \odot \mathbf{h}_{t-1},$$

Figure: FastGRNN Cell [3]



Results: CNN-AE + L1Loss

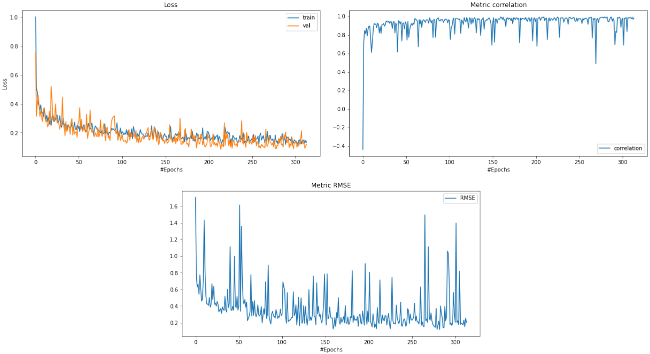
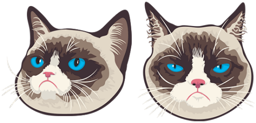


Figure: Tanh activations, MaxPool2d



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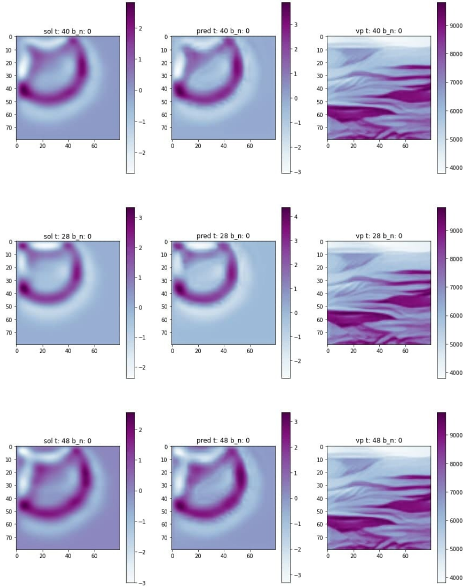
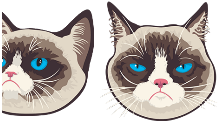




Results: RNN-GRU + L1Loss

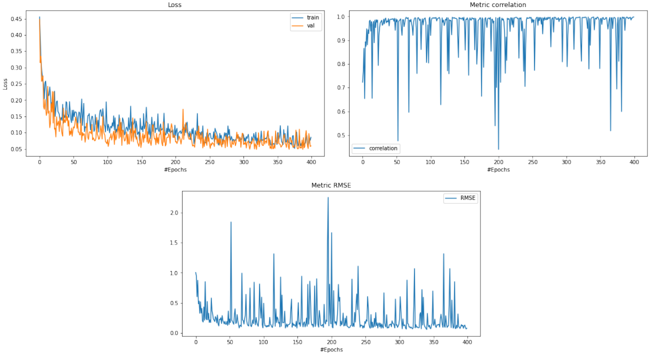
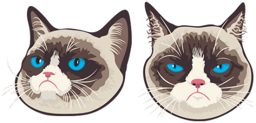
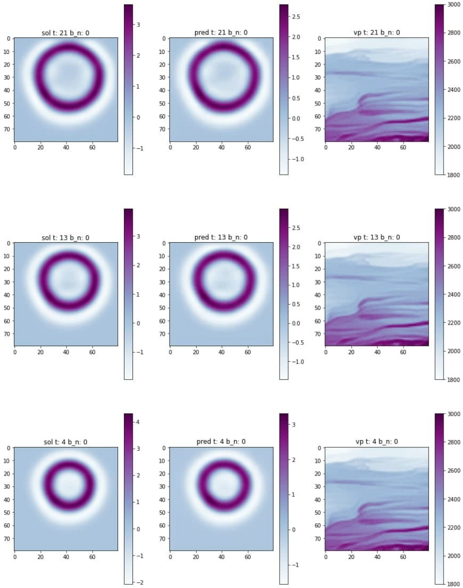
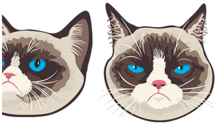


Figure: ELU activations, MaxPool2d




sol t: 21 b_n: 0
pred t: 21 b_n: 0
vp t: 21 b_n: 0
sol t: 13 b_n: 0
pred t: 13 b_n: 0
vp t: 13 b_n: 0
sol t: 4 b_n: 0
pred t: 4 b_n: 0
vp t: 4 b_n: 0
0 10 20 30 40 50 60 70
0 20 40 60
3000 2800 2600 2400 2200 2000 1800



Results: RNN-GRU + L1Loss

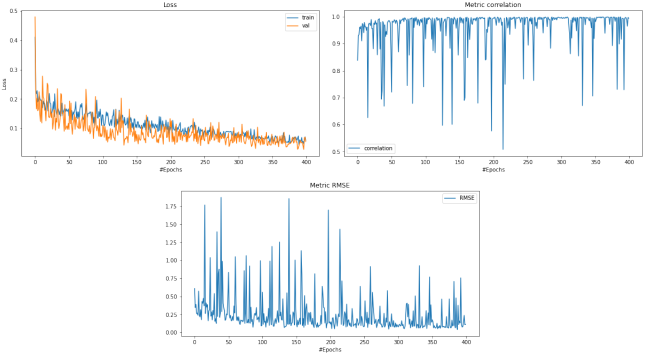
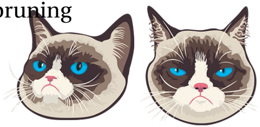
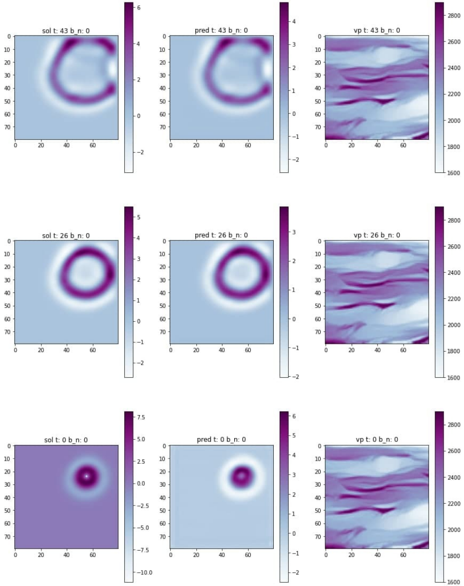
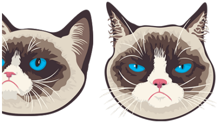


Figure: SoftPlus activations, AvgPool2d, Fast, pruning



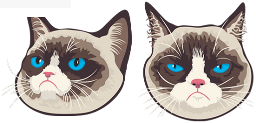
Results: CNN-AE + L1Loss





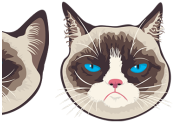
Results

	Val Loss	Correlation	RMSE
/AE/pruning_MaxPool2d_ELU_	0.047378	0.997431	0.071163
/AE/no_pruning_MaxPool2d_ELU_	0.040036	0.997193	0.078025
/AE/pruning_MaxPool2d_ReLU_	0.057838	0.996861	0.083887
/AE/pruning_AvgPool2d_ReLU_	0.051993	0.996960	0.083823
/AE/no_pruning_AvgPool2d	0.044700	0.996708	0.081910
/AE/no_pruning_AvgPool2d_Softplus_	0.055266	0.998026	0.076379
/AE/no_pruning_MaxPool2d_Soft	0.073278	0.997290	0.075836
/AE/no_pruning_MaxPool2d_ReLU_	0.067359	0.990594	0.132688
/AE/no_pruning_AvgPool2d_ReLU_	0.054532	0.997037	0.081428
/AE/no_pruning_AvgPool2d_Tanh_	0.108479	0.993235	0.116443
/AE/no_pruning_MaxPool2d_Tanh_	0.084698	0.992608	0.117035



Results

	Val Loss	Correlation	RMSE
/RNN/pruning_MaxPool2d_ELU_	0.054459	0.996234	0.084615
/RNN/pruning_AvgPool2d_ELU_	0.061728	0.997185	0.072924
/RNN/pruning_AvgPool2d_ELU_fooo__	0.056141	0.997540	0.068849
/RNN/pruning_AvgPool2d_Softplus_fast__	0.028346	0.999053	0.041984
/RNN/no_pruning_MaxPool2d_ELU_fooo__	0.048708	0.998025	0.056068
/RNN/pruning_MaxPool2d_ReLU_fooo__	0.044532	0.997466	0.068267
/RNN/pruning_AvgPool2d_ReLU_fast_	0.040655	0.998074	0.057065
/RNN/no_pruning_AvgPool2d_ELU_fooo__	0.029321	0.999008	0.043311
/RNN/pruning_MaxPool2d_Tanh_fast_	0.101255	0.991704	0.141311
/RNN/no_pruning_AvgPool2d_Tanh_fast__	0.058024	0.995073	0.082453
/RNN/pruning_MaxPool2d_ReLU_fast_	0.064585	0.995742	0.091423
/RNN/no_pruning_AvgPool2d_Tanh_fooo__	0.051936	0.998001	0.057703
/RNN/no_pruning_MaxPool2d_Tanh_fast_	0.097993	0.989757	0.120297
/RNN/no_pruning_AvgPool2d_ELU_fast__	0.075362	0.993769	0.107612
/RNN/no_pruning_MaxPool2d_Softplus_fast_	0.055147	0.996729	0.085772
/RNN/no_pruning_AvgPool2d_Softplus_fast__	0.072308	0.992906	0.116746
/RNN/no_pruning_MaxPool2d_ELU_fast_	0.094881	0.991725	0.136576
/RNN/no_pruning_AvgPool2d_ReLU_fast_	0.084444	0.986034	0.149476
/RNN/no_pruning_MaxPool2d_Tanh_fooo__	0.064734	0.995489	0.093585
/RNN/pruning_AvgPool2d_Softplus_fooo__	0.056134	0.998492	0.059784
/RNN/no_pruning_MaxPool2d_Softplus_fooo__	0.056357	0.997816	0.064815



Further work

- Additional restriction on hiddens in GRU model

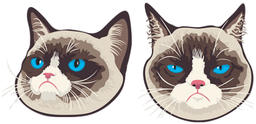
$$L_{total} = L(u_{t+1}, NN(u_t)) + \lambda L_{hidden}(h_{t+1}(u_t), encoder(u_{t+1}))$$

- FC pruning for Physic's Informed Loss net

$$W = U\Sigma V^\top$$

$$\hat{\Sigma} = \mathrm{ReLU}(\Sigma - f(s))$$

$$\widehat{W} = U\hat{\Sigma}V^\top$$



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Thank you!
Questions?