Evaluating Strike-Slip Fault Evolution with 2D CNN: Identifying the Geohazard Zones?

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1 Introduction

This project utilizes the high-resolution footage of claybox experiments (Figure 1) that analogues the development of strike-slip faults (SSF) at surface due to displacement at depth [1]. This dataset is attractive because it enable us to train a model that understand fault behavior from from the beginning to the end. In a real-world context, we can only see a single stage, and we can use the model to predict the fault maturity from a single observation in time.

Additionally, inelastic deformation via large stress/strain is not well understood. We cannot prescribe exact equations to explain failure behaviors. This project hopefully would be able to relate relevant parameters in higher dimensions to better predict different evolution stages of strike-slip faults.

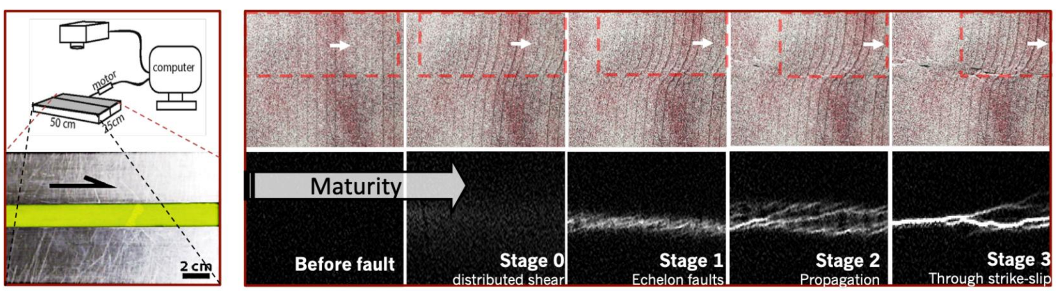

Figure 1: Claybox experiment. A box of clay is subject to external, mechanical deformation while imaged from above. Fault maturity increase (stage o - 3) with subsurface movement

2 Related work

There is no existing ML, DL study on fault stage prediction or on this dataset. Simple linear regression and best performing ridge linear regression with tuned regularization are established for baseline performance. Linear Regression is extremely overfit to training dataset (overdetermined system 128x32x3 features for 6,000 training samples). Slightly improved generalization with regularization. But model does not perform well on dev-test sets (Figure 2).

3 Dataset and Features

3 separate claybox experiments are ensembled with criteria on their distributed shear zone (1.5cm) base boundary condition, motor speed =0.5cm/min, and both deep and shallow fault depth

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	Regularization	Train MSE	Dev-Test MSE	Dev-Test Bracket Accuracy
Linear Regression	None	0.00	0.40	53%
Ridge Regression	α = 0.8	0.03	0.04	61%

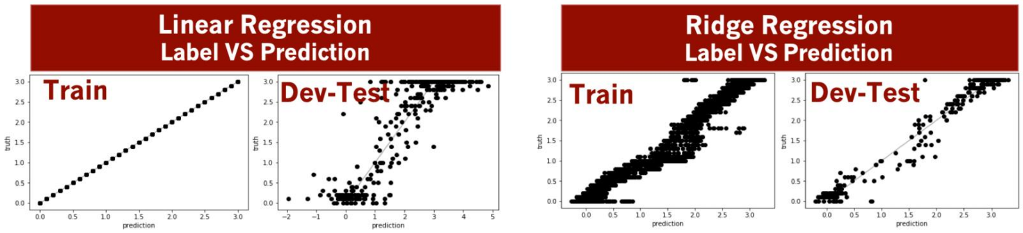


Figure 2: Baseline linear model with and without L2 regularization.

Labeling Strategy Faults are categorized in 4 discrete stages (0,1,2,3) [1]. Alternatively, I use a continuous labeling technique, only label near transition + midway, then interpolate the rest

3.1 Data Processing

- Raw physical values (.mat) of shear strain, Δu, Δv are (1) normalized for DataGenerator (and also (2) scaled for data labeling). Clipped raw image to 128x32 subimages (25% overlap), 7,500 subimages (c,u,v), 2,500 stacked images/experiment (Figure 3).
- Split $Train : Dev : Test = 0.85 : 0.10 : 0.05$
- Image Augmentation: I experimented and found augmentation combination that best generalizes SSF geometry related to input size and characters: zoom_range=0.1, horizontal_shift and vertical_shift=0.2, horizontal and vertical flips, all are randomly applied using keras.ImageGenerator

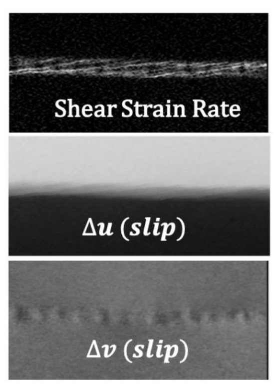


Figure 3: Model input comprised of 3 channels of physical values representing geometry and slip.

4 Methods

4.1 2D-Neural Network Architectures and Hyperparameters

Both shallow and deeper CNNs (added dilation) are explored(Figure 4).**Hyperparameters** explored are *number of layers, NC_filter, learning rate, *dilation_rate, BN_momentum, *scaling of image augmentation. The asterisk indicated parameters that influence more on model performance than another.

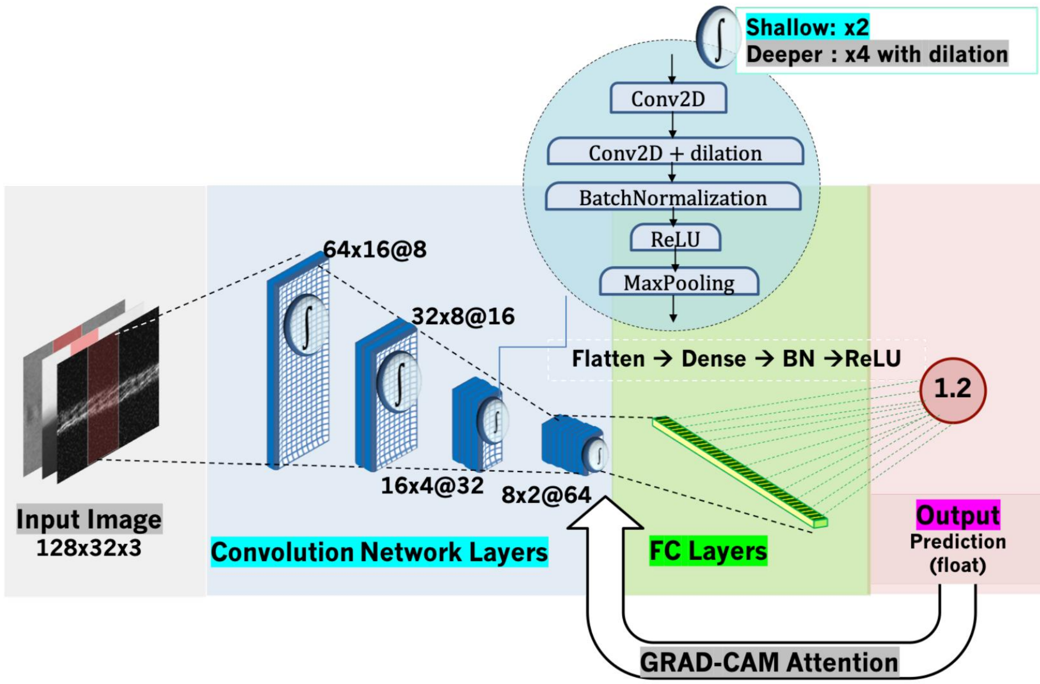
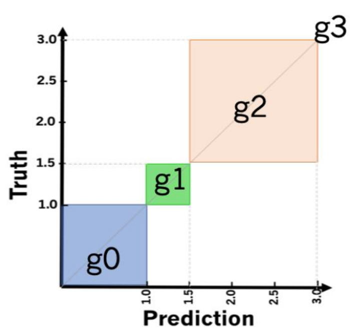


Figure 4: CNNs Model Architecture

4.2 Bracket Loss Function and Bracket Accuracy

MSE is a reasonable metrics for regression problem. However, for this dataset, I defined a 'Bracket Loss' (Figure 5), which still incorporate MSE but also add extra penalization to predictions that fall outside their characteristic groups (g0, g1,g2, g3). Co-efficient terms or choices of adding alone or adding with square are tuned during training.



$$\mathcal{L} = mse + (g0)^2 + (g1)^2 + (g2)^2 + g3$$

$$\begin{array}{ll} y<1 & : g0 = \max(0, \hat{y} - 1) \\ 1 \le y < 1.5 & : g1 = \max(\max(1 - \hat{y}, 0), \max(0, \hat{y} - 1.5)) \\ 1.5 \le y < 3.0 & : g2 = \max(\max(1.5 - \hat{y}, 0), \max(0, \hat{y} - 3.0)) \\ y = 3 & : g3 = \max(0, 3 - \hat{y}) \end{array}$$

Figure 5: Defining Bracket Loss Function

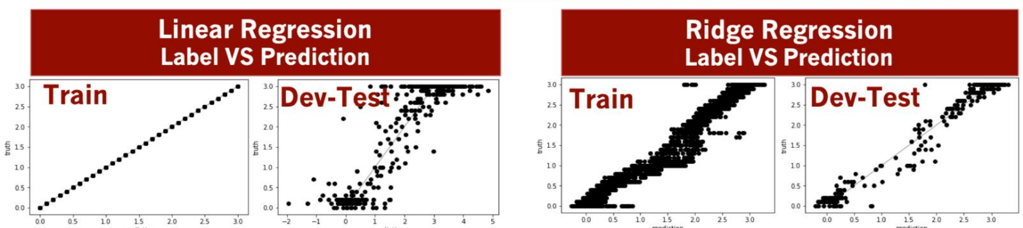
5 Experiments/Results/Discussion

5.1 Experiments and Results

Tested Models	Params	MSE		Bracket Loss		Bracket Accuracy	
		Train	Test	Train	Test	Train	Test
2D CNN : shallower Bracket Loss	AdamOptimizer, Lr = 5e-3 Epoch=50, Batch-size = 32 momentum = 0.8	0.038	0.024	0.029	0.048	81.19%	85.82%
2D CNN : deeper Dilation + Augmentation + Bracket Loss		0.031	0.022	0.036	0.026	87.55%	89.80%
2D CNN : deeper Dilation + Augmentation + MSE		0.027	0.020	0.051	0.028	74.60%	67.55%

The deeper CNN is the best performing model as measured by test accuracy and loss. We choose to use the bracket loss as the main objective of this project for both shallow and deep CNNs. The third experiments using basic MSE on deeper CNNs show poor performance, indicating that the bracket loss better reflects my scientific objective.

	Regularization	Train MSE	Dev-Test MSE	Dev-Test Bracket Accuracy
Linear Regression	None	0.00	0.40	53%
Ridge Regression	$\alpha = 0.8$	0.03	0.04	61%



5.2 Grad_CAM Attention Map

I used a Github repo [3] as a starter code for visualizing the last convolutional unit that influences the prediction [2] (Figure 6).

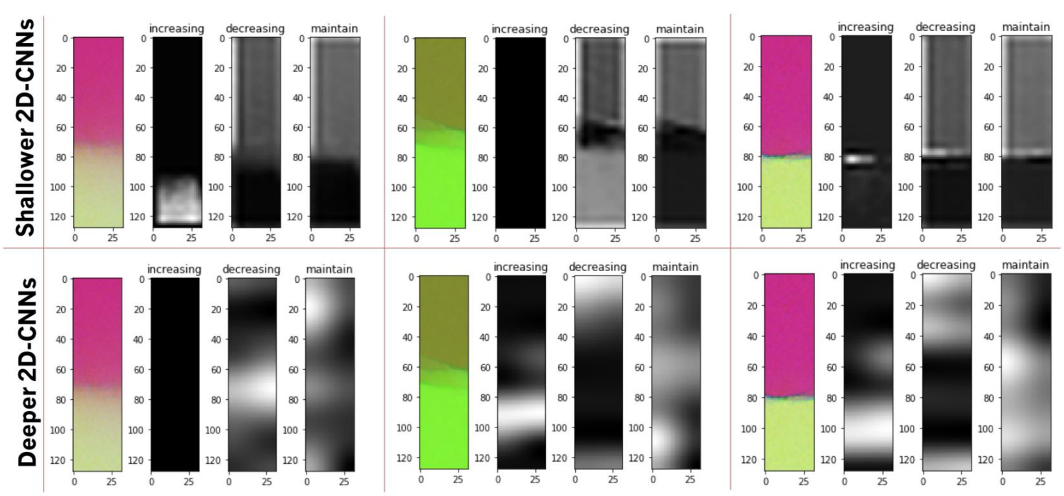


Figure 6: GradCAM attention map from shallower and deeper CNNs.

5.3 Discussion

- The deeper CNNS outperforms shallow CNNs, due to image augmentation designed to scaled and shift faults away from center dilation_rate applied to help handle it.
- GRAD_CAM Attention [2] helped identify models during development that did not look at the faults to make predictions. It will be important for future architecture choices. Though, deeper CNNs perform better, the shallower CNNs' attention maps are more interpretable.

6 Conclusion/Future Work

The CNNs models are able to predict fault maturation stages with greater than 86% and 89% accuracy in shallower and deeper models, a significant improvement from baseline.
GRAD_CAM attention maps are useful to understand the model I build and work with inside out, and will influence choices of model architecture and hyperparmeters

Future Work I hope to better understand how CNNs make prediction, go deeper into attention map, hopefully to identify empirical relationships for fault deformations. If possible, try to detection and localization (YOLO) problems based on magnitude of displacement, which will remove the subjective labeling stage from geologists. Lastly, apply model to real-world example with appropriate dataset such as submarine topography, terrestrial LiDAR .

7 Code

The code to data preparation and my CNNs models are available on Github:
`https://github.com/laainam/data_prep`
`https://github.com/laainam/model`

References

[1] Alexandra E. Hatem, Michele L. Cooke, and Kevin Toeneboehn. Strain localization and evolving kinematic efficiency of initiating strike-slip faults within wet kaolin experiments. *Journal of Structural Geology*, 2017.

[2] Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. In *Proceedings of the IEEE International Conference on Computer Vision*, 2017.

[3] Kotikalapudi, R. & contributors (2017) *https://github.com/raghakot/keras-vis*