Predicting microseismic event density during hydraulic fracturing from surface seismic with gradient boosted trees

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Summary

With the objective of understanding which surface seismic variables contribute to increased microseismicity in an unconventional reservoir during completions, a set of 20 surface seismic features was used to establish a predictive relationship to a microseismic event density independent variable. The gradient boosted trees algorithm was selected to build the regression model. The majority of microseismic event density variance is described by only two surface seismic features: VVAz percent velocity anisotropy and VVAz velocity anisotropy azimuth. The predictive model was applied to a new well set and notable variance in expected microseismicity was observed.

Method

The dataset consists of an event catalogue for a 3 well microseismic program acquired during hydraulic fracturing, and a coincident 3D surface seismic volume. At each surface seismic bin, the total count of microseismic events were summed to provide a map of microseismic event density (Figure 1).

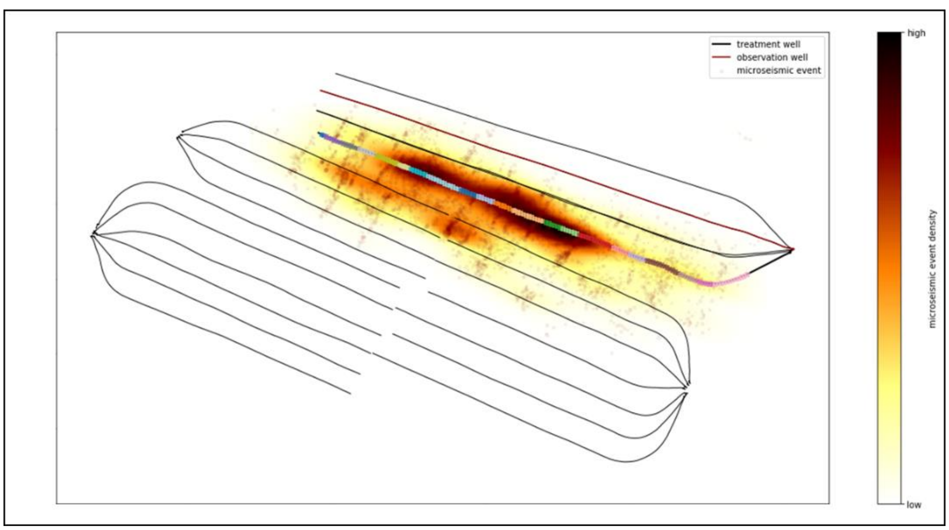

Figure 1. Single well microseismic event density map

Maps from various stratigraphic levels within the unconventional reservoir were generated for a 3D seismic volume. Seismic inputs included: stack seismic reflection amplitudes, VVAz velocity anisotropy magnitude and direction, AVAz Ruger parameterizations, and seismic inversion elastic properties, providing 32 total maps. Two additional features were added: the distance to well for each seismic bin and a random number to act as placebo control. The set of 34 features was pared down to 20, by removing multicolinear variables. The multicolinearity convention used was a Pearson correlation greater than 0.7; the final set of variables is shown in Figure 2.

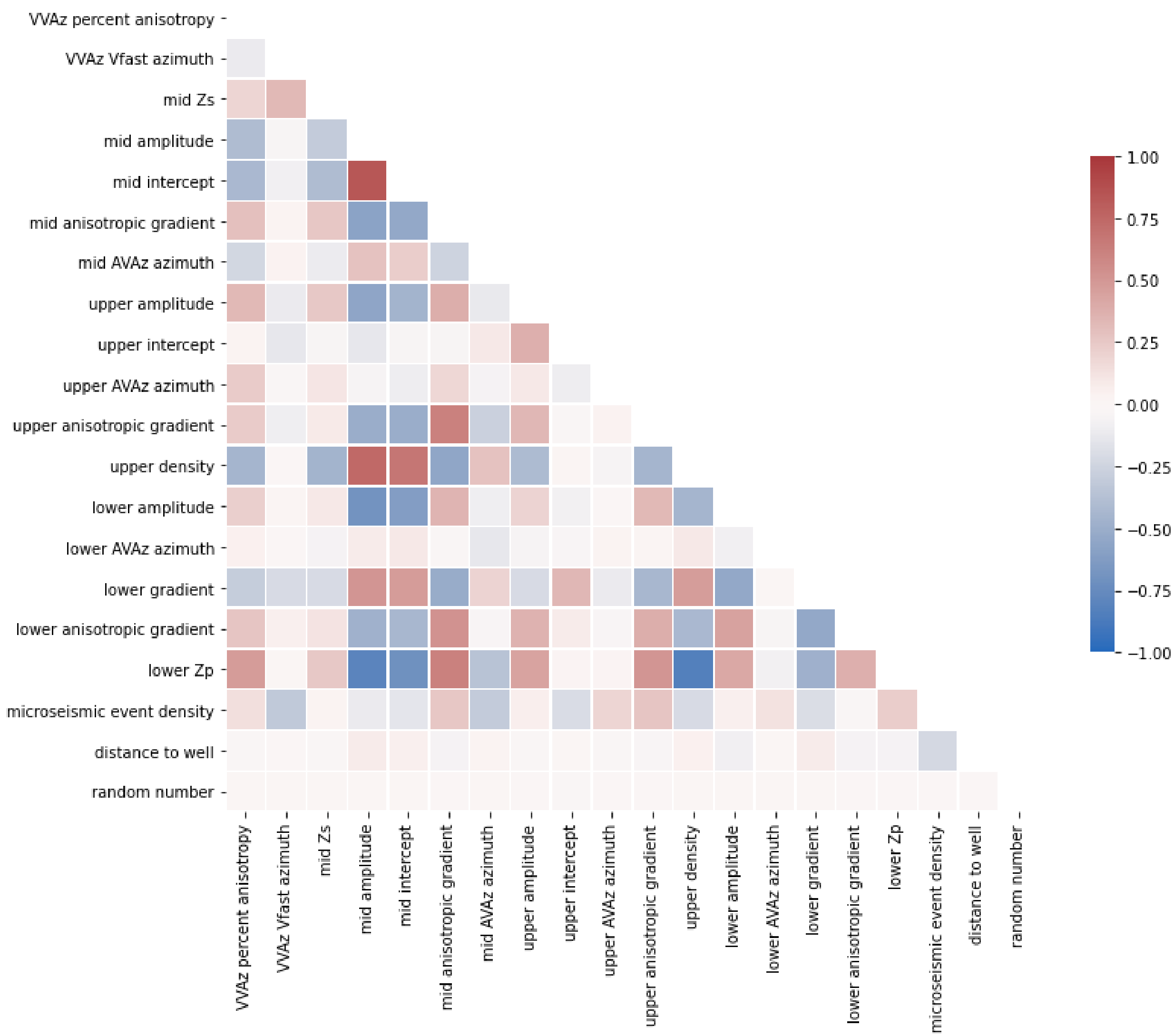

Figure 1. Final feature set correlation matrix, coloured by Pearson R

A gradient boosted tree-based regression with standard hyperparameters was trained on a 66% training subset to generate a model which takes seismic variables as input, and predicts microseismic event density upon output. This approach was chosen because it is robust to outliers, does not require significant feature engineering effort, and is not predisposed to overtraining.

Results

An actual versus predicted microseismic event density scatterplot (Figure 3) suggests that surface seismic data are able to explain variance in microseismic outcomes. On average, the predicted microseismic density has 20% error for blind testing data. That is, we can predict microseismic event density to within 20% using surface seismic data alone.

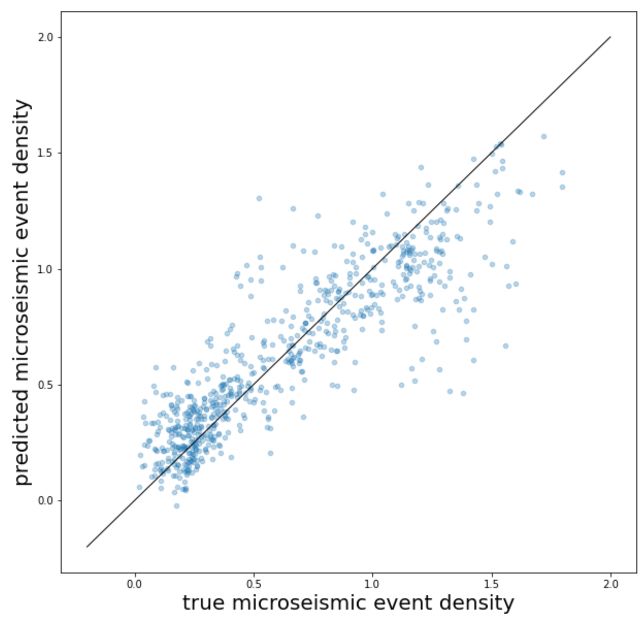

Figure 3. Testing subset, actual versus predicted microseismic event density

Figure 4 shows the actual microseismic event density, and predicted microseismic event density for a single well. 66% of the shown data are training data, and the rest are blind to training. The general trends of microseismicity are well preserved across the predictive model, with regions of low event density and high density both being predicted correctly.

Once trained, the regression model can be applied field-wide to forecast expected microseismicity for new wells. A single pad's expected microseismicity is shown in Figure 5.

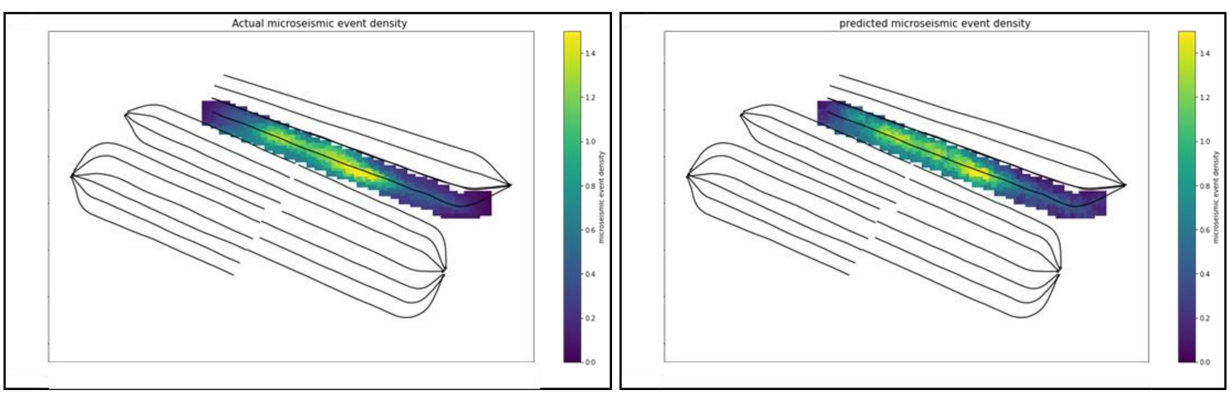

Figure 4. Actual and predicted microseismic event density for a single well event catalogue

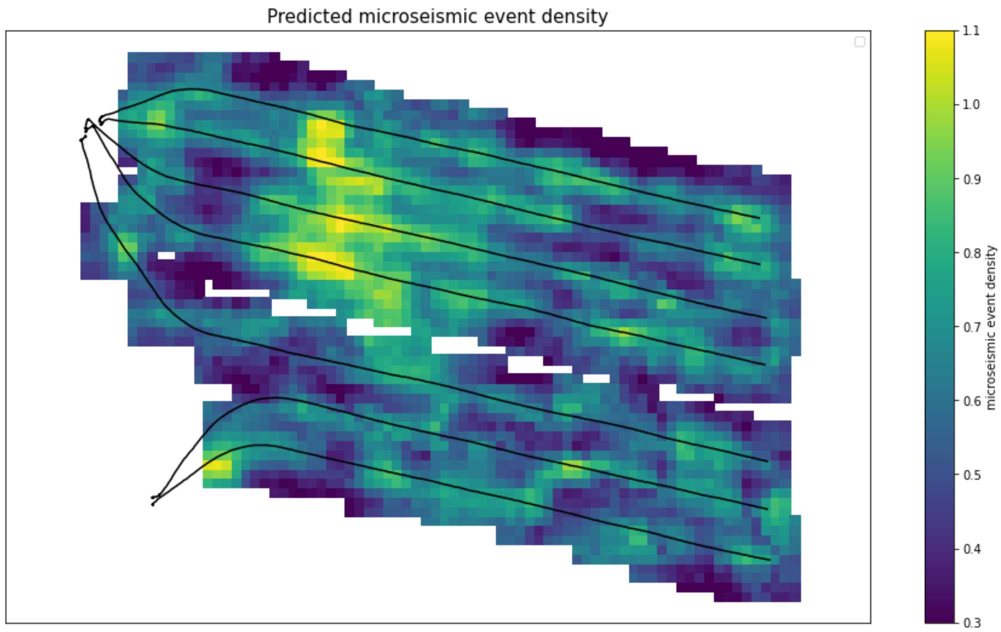

Figure 5. Predicted microseismic event density for a set of new wells

To determine which seismic maps contributed the most to variance in microseismic event density, permutation importance was calculated for the test set (Figure 6). The most important variable in the feature set, was the distance from the seismic bin to the stimulation well; nearer seismic bins show higher microseismic event density (Figure 7a). The VVAz velocity anisotropy magnitude and direction rank second and third respectively in the importance hierarchy. Microseismic event density increases with increased velocity anisotropy and there is a minimum expectation of microseismicity when fast velocity direction is ~110° from geographic North (Figure 7b & 7c).

Together, these three variables explain a majority of observed differences in microseismicity.

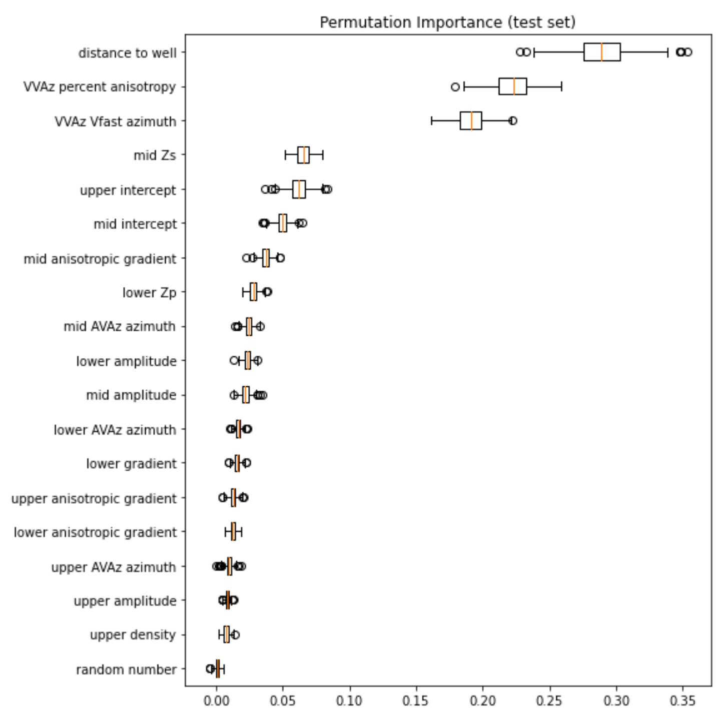

Figure 6. Testing subset permutation importance for regression model

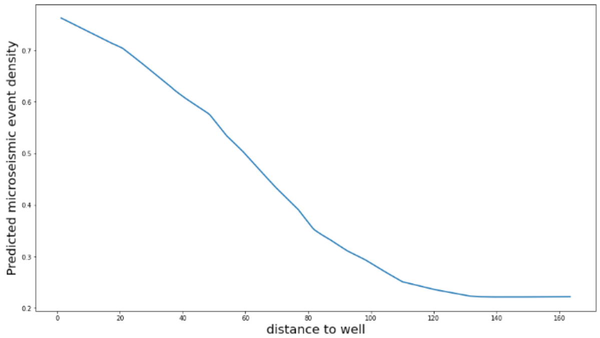

Figure 7a. Distance to well versus microseismic event density

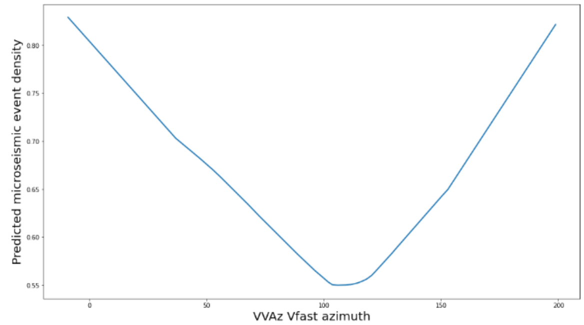

Figure 7c. VVAz fast velocity azimuth versus microseismic event density

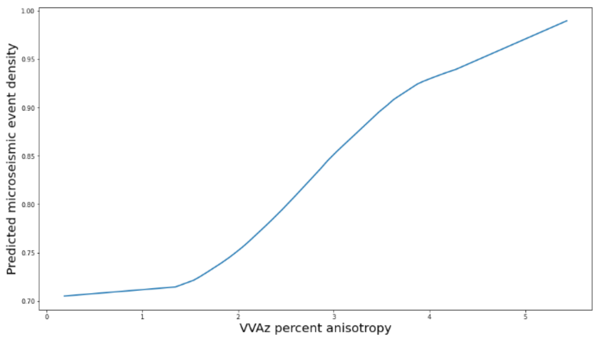

Figure 7b. VVAz percent velocity anisotropy versus microseismic event density

Conclusions

A regression model was trained to predict hydraulic fracturing microseismic event density using surface seismic. The model was able to predict event density within 20% for blind testing data. The most important prediction variable from the surface seismic was VVAz velocity anisotropy and azimuth.

References

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