PRODUCTION TIME SERIES – CONTROL AND PREDICTION OF PROCESS ERROR

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PROJECT OVERVIEW & GOALS

Overview:

- Customer has come to me with a dataset that gives historical run sequence through several toolsets suitable for time series lagging. (detailed descriptions provided in "Data Dictionary.txt" on Github)
- The process uses statistical process control in a manufacturing environment.
- The key starting assumption from the customer is that other noise/error sources are not important and this assumption may not be true.

• Key Goals:

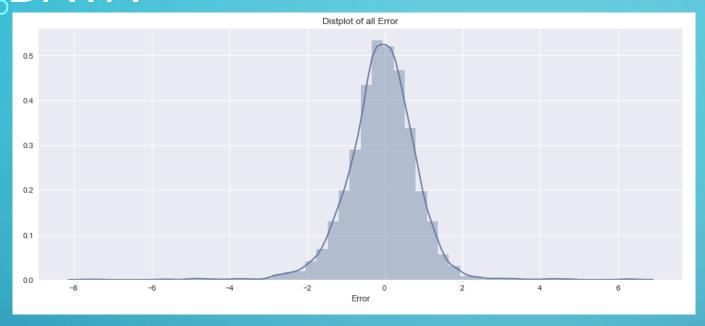
- Find any correlations between lagged data and larger |Error| which would be suitable for implementation of run rules in the production line (i.e. prevent these sequences from occurring).
- Determine if any models can be developed to predict Error based on previous runs through the tool under the assumption of no other dominant error sources.
- Advise on next steps to improve modeling capability

DATA CLEANING

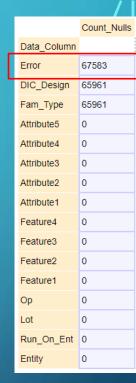
Cleaning:

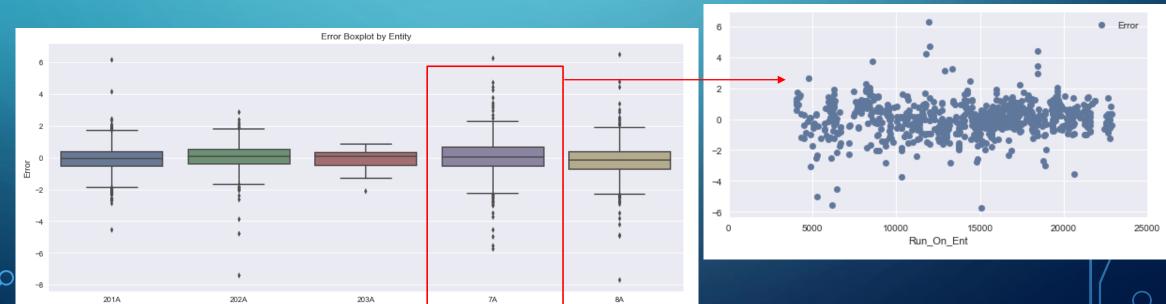
- Customer supplied dataset contains a large anonymized dataset of time series sequence through several identical toolsets.
- Timestamps are removed and converted to sequential runs, thus protecting IP metrics.
- Error columns were normalized to zero
- Error is available for smaller subset of the data, but the entire run history is relevant for lagging previous runs, thus NaN were not removed/altered prior to lagging. The key features/attributes of previous 'lagged' runs is what is being correlated to each instance of Error.
- See "final_text" on Github for more explicit summary

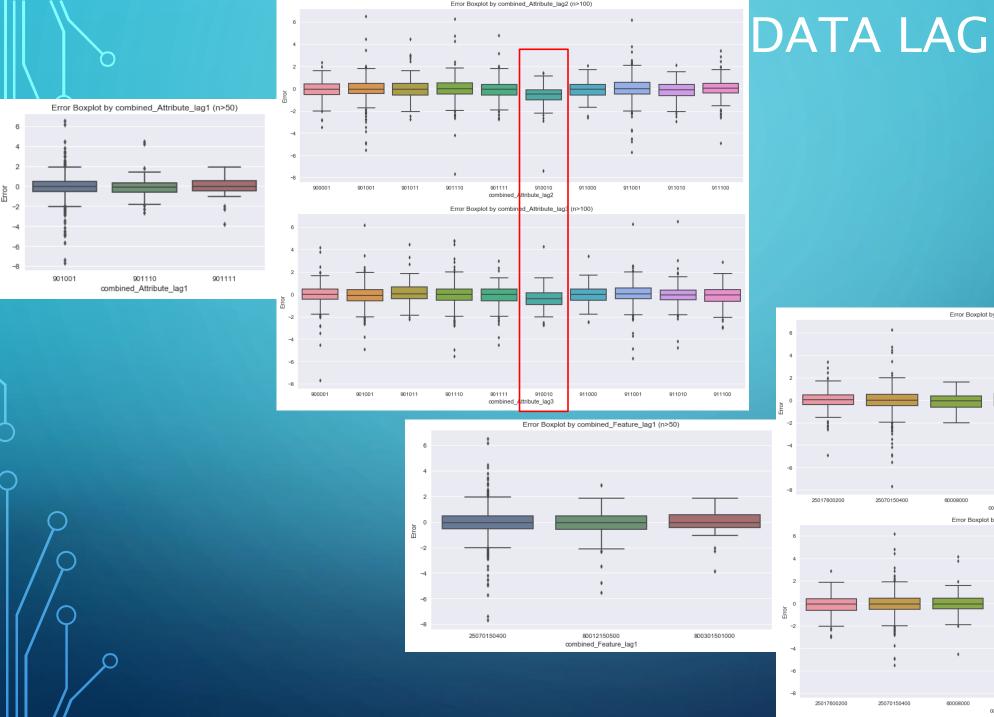
DATA



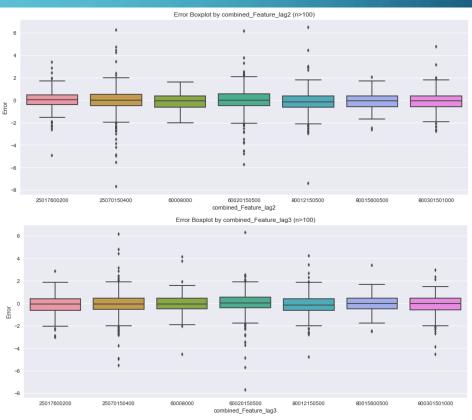
Entity







DATA LAG SUMMARY



TUKEY HSD - 910010

```
mc = MultiComparison(CAL2['Error'], CAL2['combined Attribute lag2'])
Multiple Comparison of Means - Tukey HSD, FWER=0.05
group1 group2 meandiff lower
900001 910010
               -0.518
901001 910010
              -0.5299
                       -0.8072 -0.2526
901011 910010 -0.5594
                       -0.8673 -0.2515
901110 910010 -0.5653
                       -0.8429 -0.2878
901111 910010 -0.4675
                       -0.7425 -0.1926
               0.462
910010 911000
                        0.1126 0.8113
910010 911001
               0.5879
                        0.3159
910010 911010
              0.4072
                        0.1115
910010 911100 0.6203
                        0.3352 0.9054 True
 ['900001' '901001' '901011' '901110' '901111'
 '911010' '911100']
mc = MultiComparison(CAL3['Error'], CAL3['combined Attribute lag3'])
Multiple Comparison of Means - Tukey HSD, FWER=0.05
group1 group2 meandiff lower
900001 910010 -0.3634
                       -0.6291 -0.0977
901001 910010
               -0.325
                       -0.5723 -0.0777
901011 910010
              -0.5151
                       -0.8247 -0.2055
901110 910010 -0.3872
                       -0.6374 -0.1369
901111 910010 -0.3309
                       -0.5951 -0.0666
910010 911001
              0.4425
                        0.1761 0.7088
910010 911010
               0.336
                        0.0526
910010 911100 0.2823
                        0.0138
 '900001' '901001' '901011' '901110'
 '911010' '911100']
```

Customer has clear outlier for one particular combined attribute (910010):

Recommendation to investigate run rules to prevent this sequence and improve overall control of process error.

PREDICTION

Model:	Linear SGD	Linear Lasso	Linear Ridge
CV MSE score	0.9238	0.9341	0.9231
explained variance	0.0218	0	0.0234
R ² coef of determination	0.0215	-0.0003	0.0232

Model:	Random Forest	SVM poly	kNN
CV MSE score	0.8714	0.8714	0.9152
explained variance	-0.1319	0.0028	0.0054
R ² coef of determination	-0.1395	-0.0155	0.0053

All models indicate good fitting but very low explained variance. Likely cause is unaccounted for noise sources in the data.

SUMMARY

- Goals and assumptions:
 - Find any correlations between lagged data and larger |Error| which would be suitable for implementation of run rules in the production line.
 - See if any models can predict Error based on previous runs through the tool.
 - Key initial assumptions: other noise/error sources are not important (may/may not be true)
- Findings and recommendations:
 - very strong outliers in the Error found that are suitable to perform DOE to prove run rules are indeed needed. *Customer was able to confirm this with DOE and begin pilot to prevent occurrence
 - Regressions yield models w ~0.9 MSE and are scores are reproducible on test
 - none of the models are very good at explaining variance in the data. Conclusion is that the assumption of other noise/errors sources being unimportant is likely false. Recommendation to further improve the model is to retrieve other sources of data that can me incorporated into the model.
 - Recommendation for next phase of modeling is to incorporate Heat maps of optical emission spectra for the fixed setup run (aka lag1) and each critical plate that measures Error.