

Complexity Challenges to the Discovery of Relationships in Eddy Current Non-destructive Test Data



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Outline

- Background Information
- Eddy Current Non-destructive Tests (NDT)
- Approach
- Algorithms
- Results
- Interpretation of Results
- Conclusions
- Future Research
- Questions



Background

1 of 2

- Many commercial & military aircraft reached or exceeded original design life
 - *USAF aircraft 20-35+ years old*
 - *KC-135 (40 yrs. old) extended for 25 years*
 - *Civilian airlines Boeing 727 family – Introduced in 60's*
- Corrosion is a serious threat especially to older aircraft
 - *Significant increase in maintenance costs*
 - *Increasing concern about structural integrity*

Background

Aloha Flight 243

2 of 2



Relationship Hypothesis

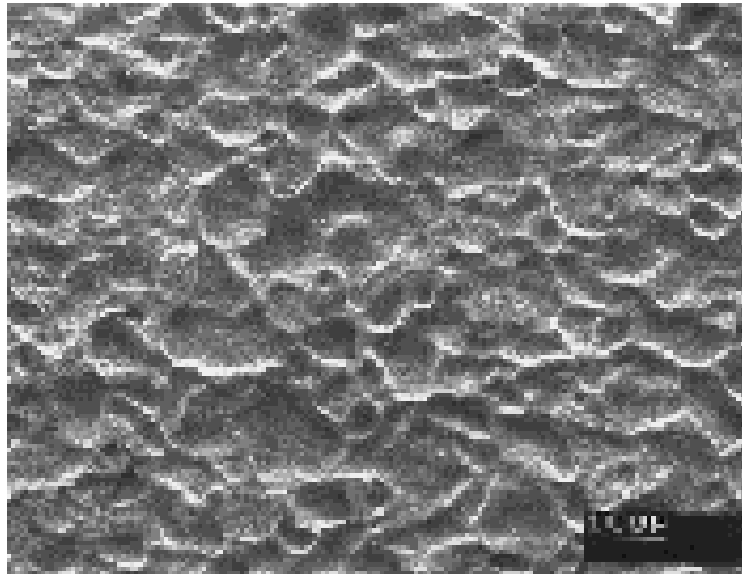
1 of 2



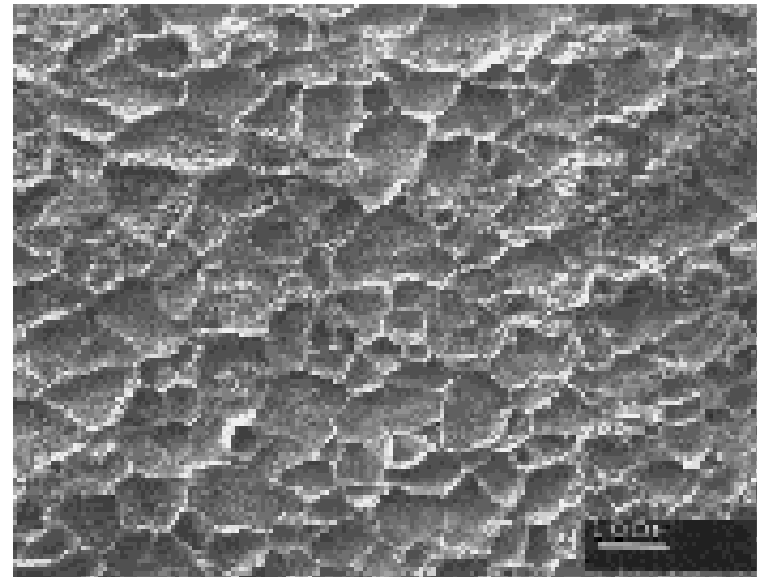
- Relationship between calibration specimen results & classifying corrosion on KC-135 parts
- Current artificial corrosion processes show similar characteristics as those found in naturally corroded lap joints

Relationship Hypothesis

2 of 2



Natural Corrosion
(*KC-135 Specimen*)



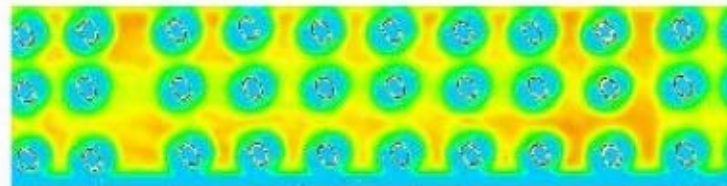
Artificial Corrosion
(*Calibration Specimen*)

Eddy Current Non-destructive Tests



- Problems with current visual representation
 - *Requires considerable expertise to create and interpret*
 - *Need for visual clarity leads to data generalization, averaging, or overlooked points ~ accuracy?*
 - *Missed corrosion may cause a catastrophic accident*

ACDP A2 Region 1 scanned at 2Khz



Deeper orange colour is suspect area

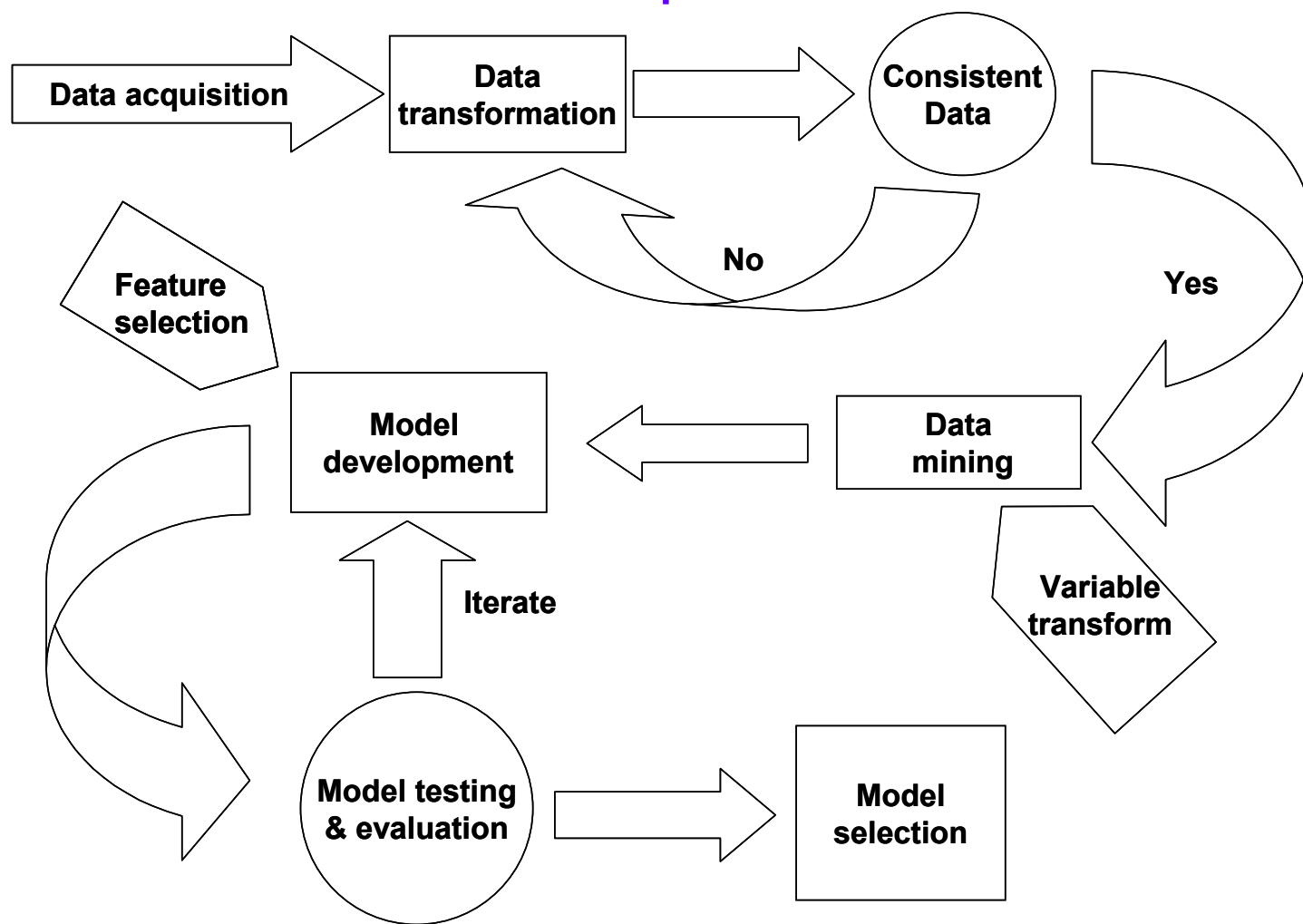


Approach Outline

- Data acquisition
- Data transformation & consistency
- Model development & feature selection
- Model training & testing
- Model Evaluation
- Model Selection



Approach Graphic

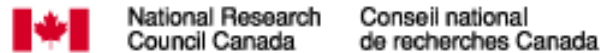




Approach

Data Acquisition

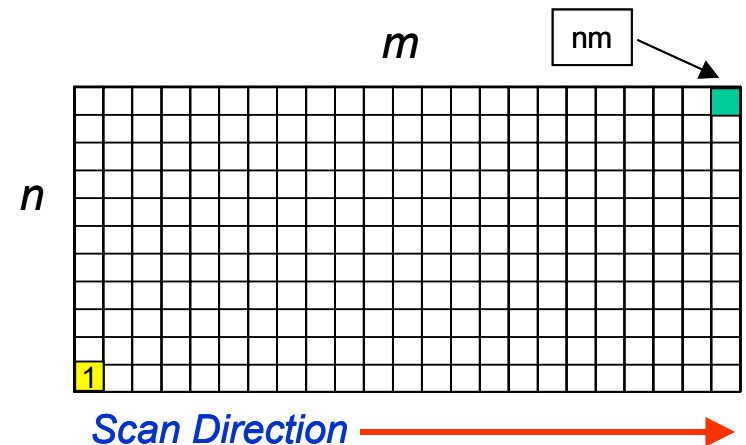
- Institute of Aerospace Research



- Calibration specimens
- Retired KC-135 specimens

- Data

- Induced Voltage measurements from multi-frequency scans
- Calibration specimen E1



Approach



Data Transformation & Consistency

1 of 5

Eddy Current Specimen E1 data

- 4 different scan frequencies are the 4 predictor variables (5.5 kHz, 8 kHz, 17 kHz, & 30 kHz)*
- Merged 4 scan frequency files into one file*

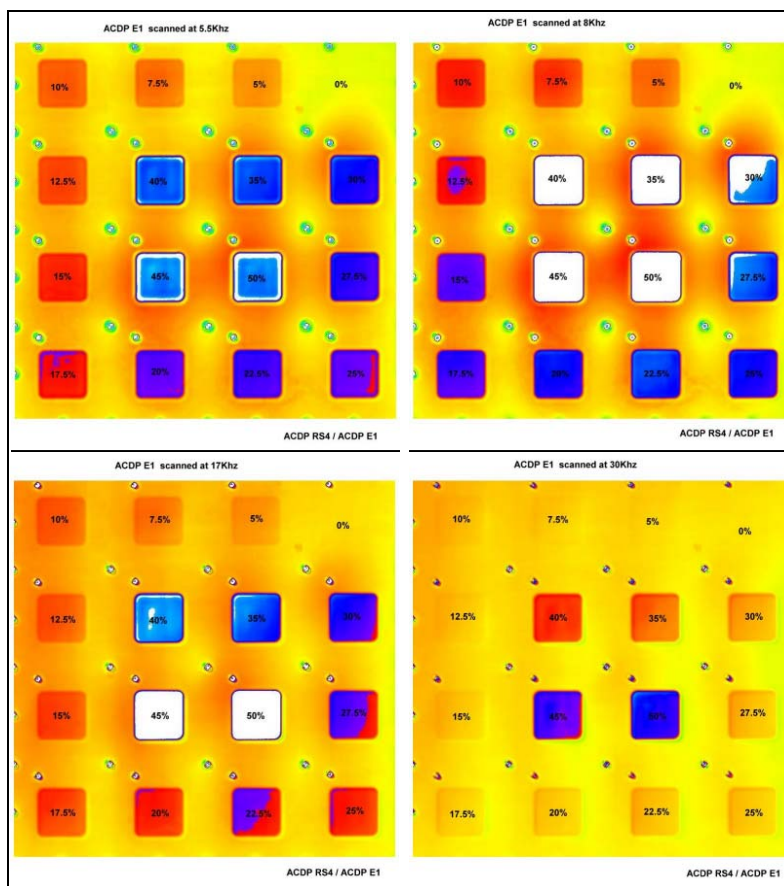


Approach

Data Transformation & Consistency

2 of 5

5.5 kHz



8 kHz

17 kHz

30 kHz

Approach

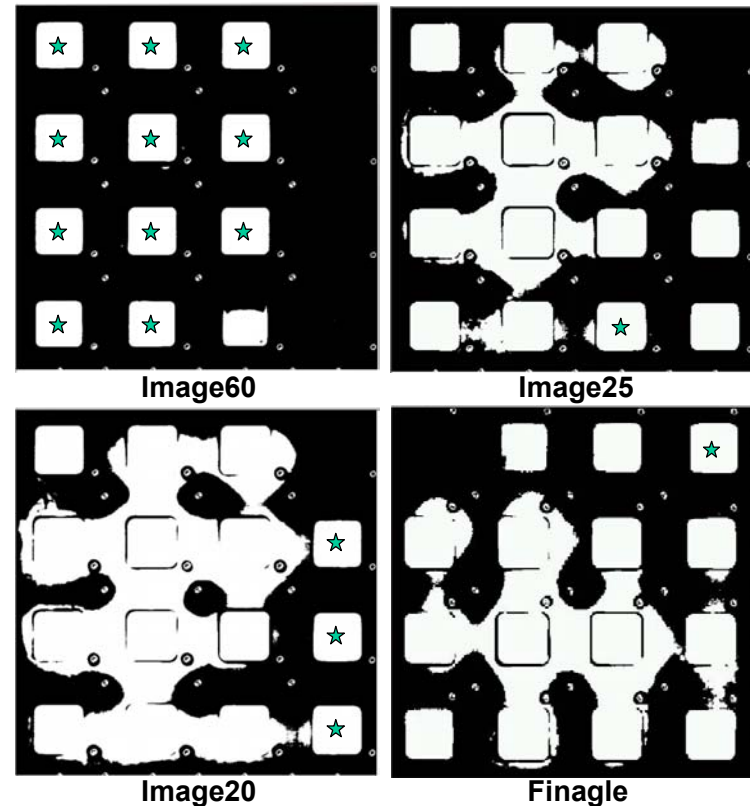
Data Transformation & Consistency

3 of 5



Results from PicView Program

Starred areas show which picture is used to model specific loss area.

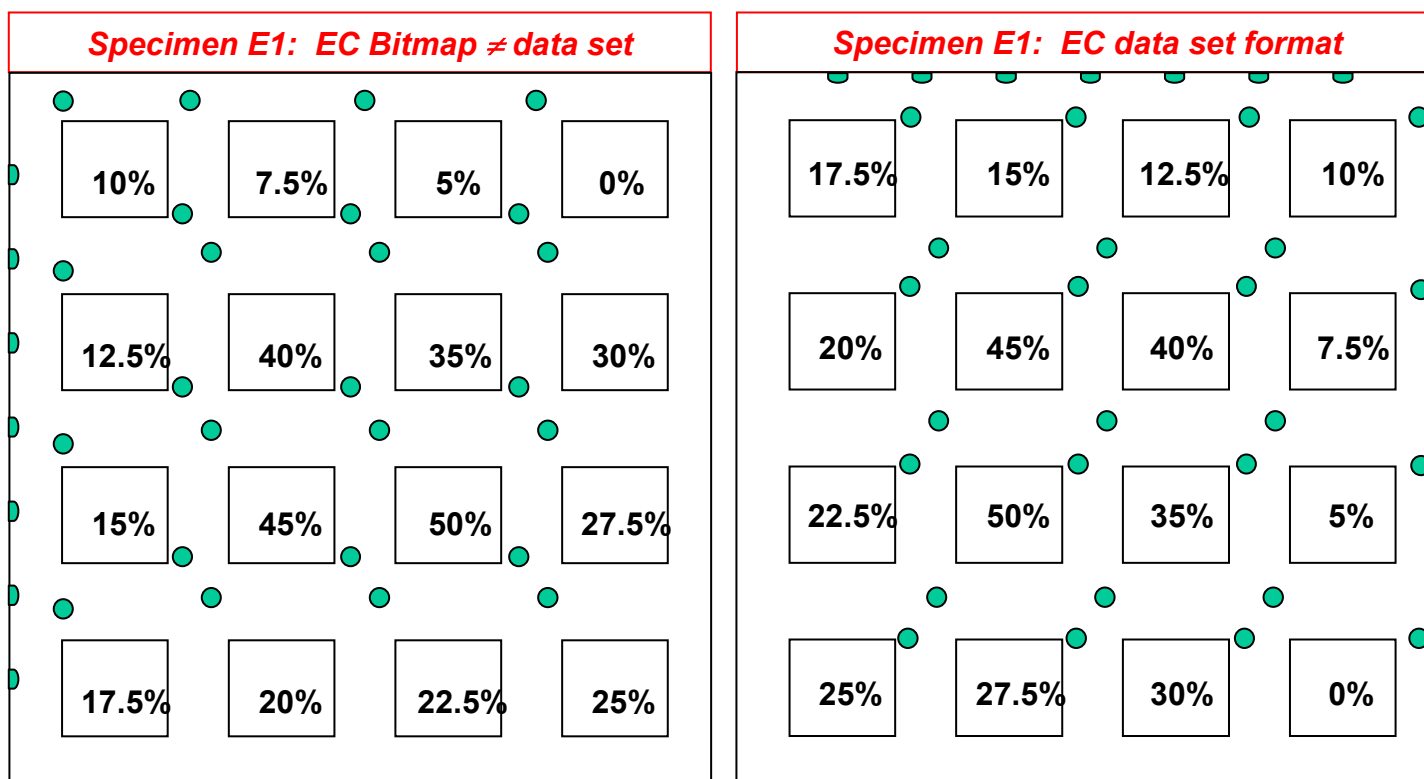




Approach

Data Transformation & Consistency

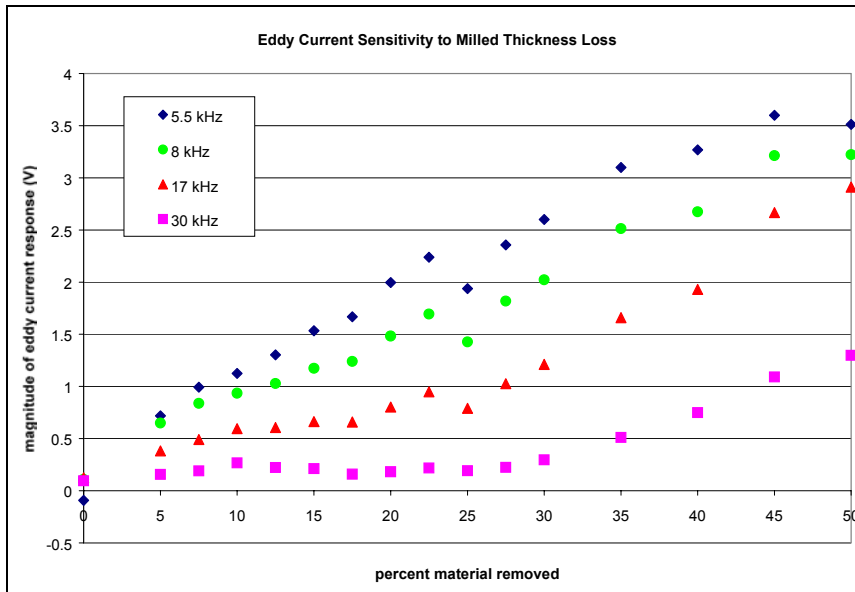
4 of 5



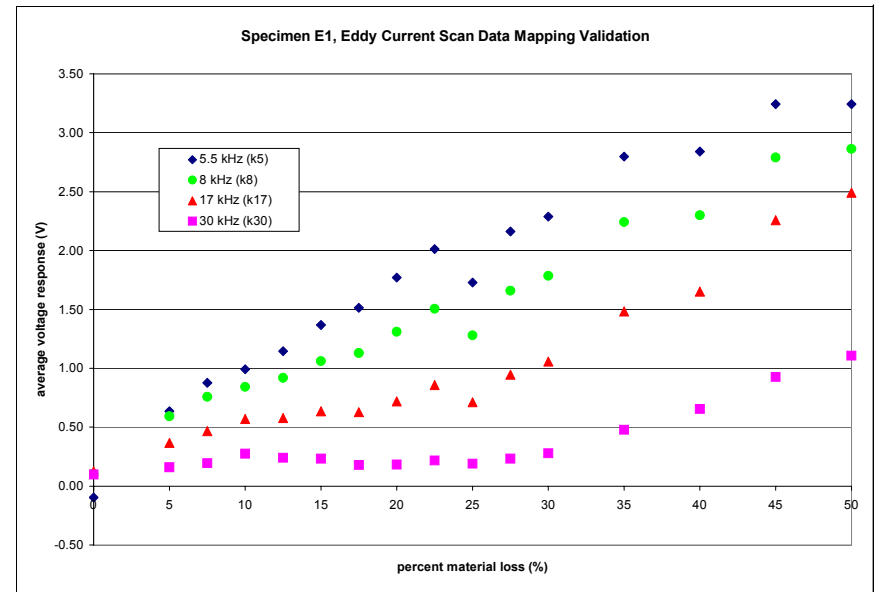
Approach

Data Transformation & Consistency

5 of 5



Graph from original study



Graph resulting from data transformation



Approach

Model Development & Feature Selection

- Eddy Current
 - Four predictors and one response variable
 - Looked at histograms of variables to categorize the observation's distribution
 - Used scaling and transformations of predictors
- Feature Selection (E.G., regression)
 - Stepwise, Forward, Backward selection
 - Maximum R^2_{adj} , Mallows CP



Approach

Model Training & Testing

- Calibration specimen data used for training ~ Eddy Current specimen E1
- Training and Test data configuration (in general)
 - 75% training (120,456 observations)
 - 25% test (40,152 observations)



Approach

Model Training Evaluation

- Akaike Information Criterion
- Schwartz Criterion
- Coefficient of multiple determination (R^2)
- Adjusted R^2
- Mallows C_p
- Mean Absolute Error
- Mean Squared Error



Approach

Model Selection

Selection of best modeling methodology based on root mean squared error calculation on test set

$$\sqrt{MSE_{TESTSET}} = \sqrt{\frac{1}{N} \sum_{j=1}^N (y_j - \bar{y})^2}$$



Algorithms

1 of 4

Multiple Regression

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \dots + \beta_{p-1} X_{i,p-1} + \varepsilon_i$$

Considered polynomial, interaction, and transformed terms

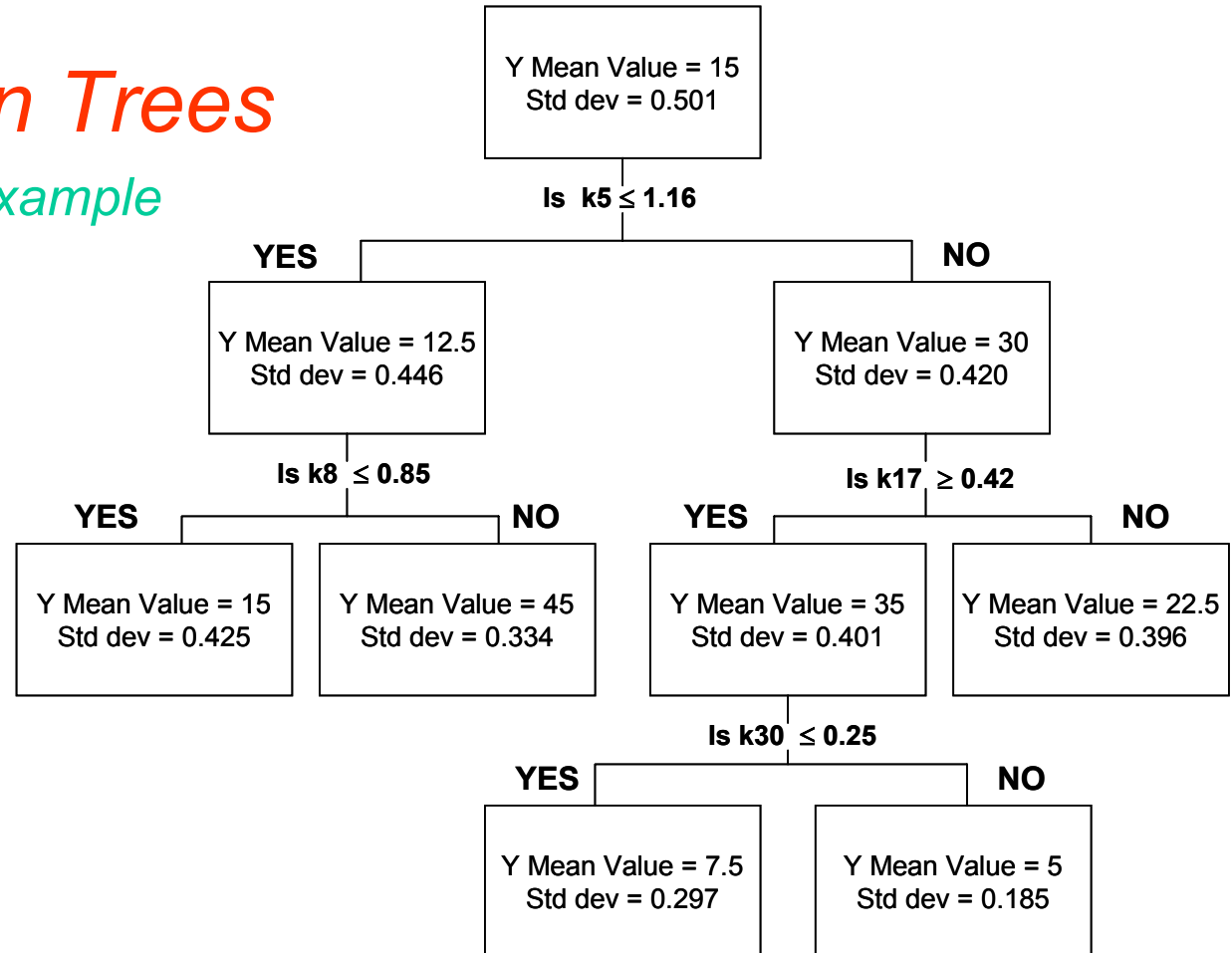
Algorithms

2 of 4



Regression Trees

Least Squares example

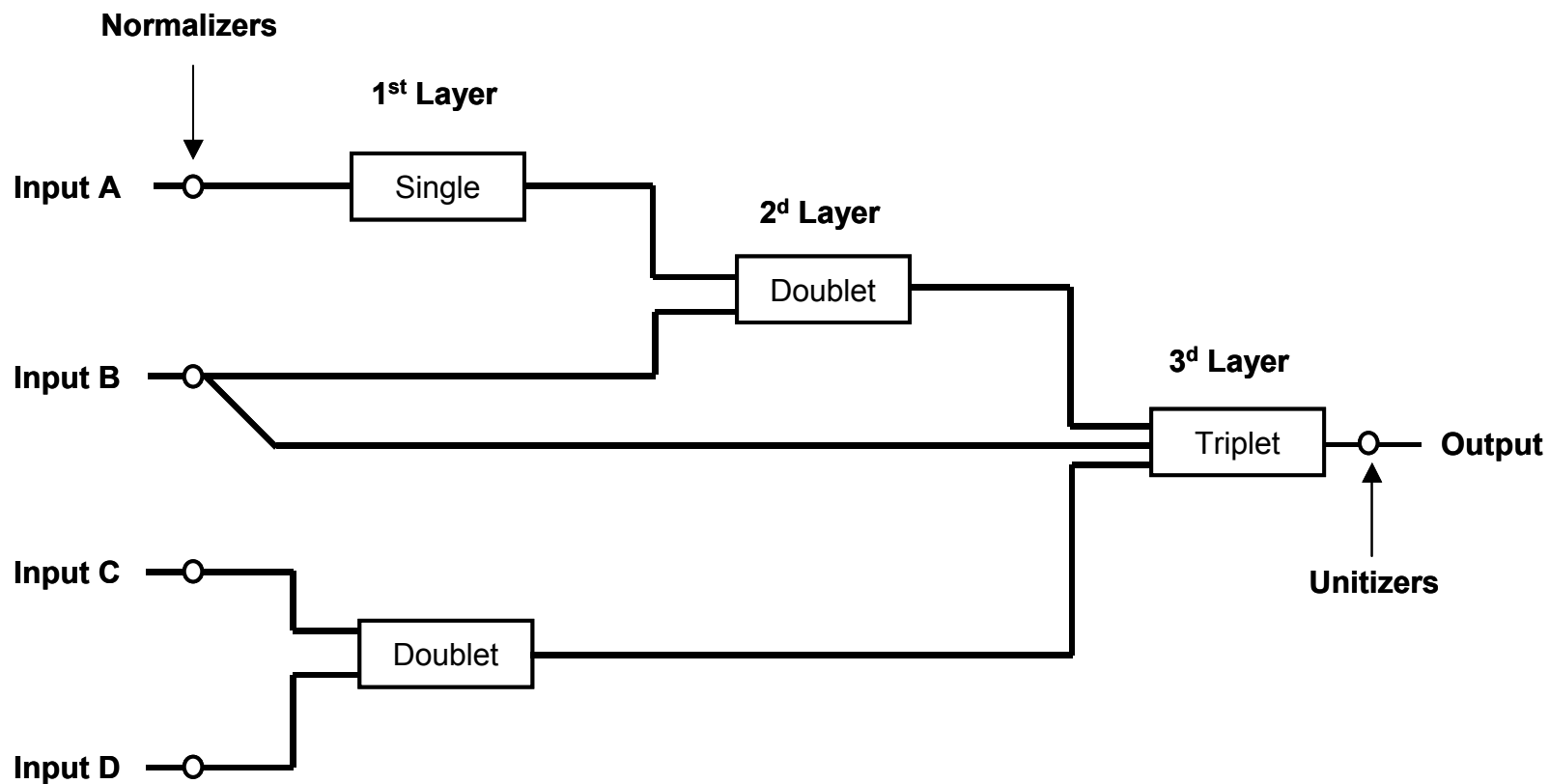




Algorithms

3 of 4

Polynomial Networks

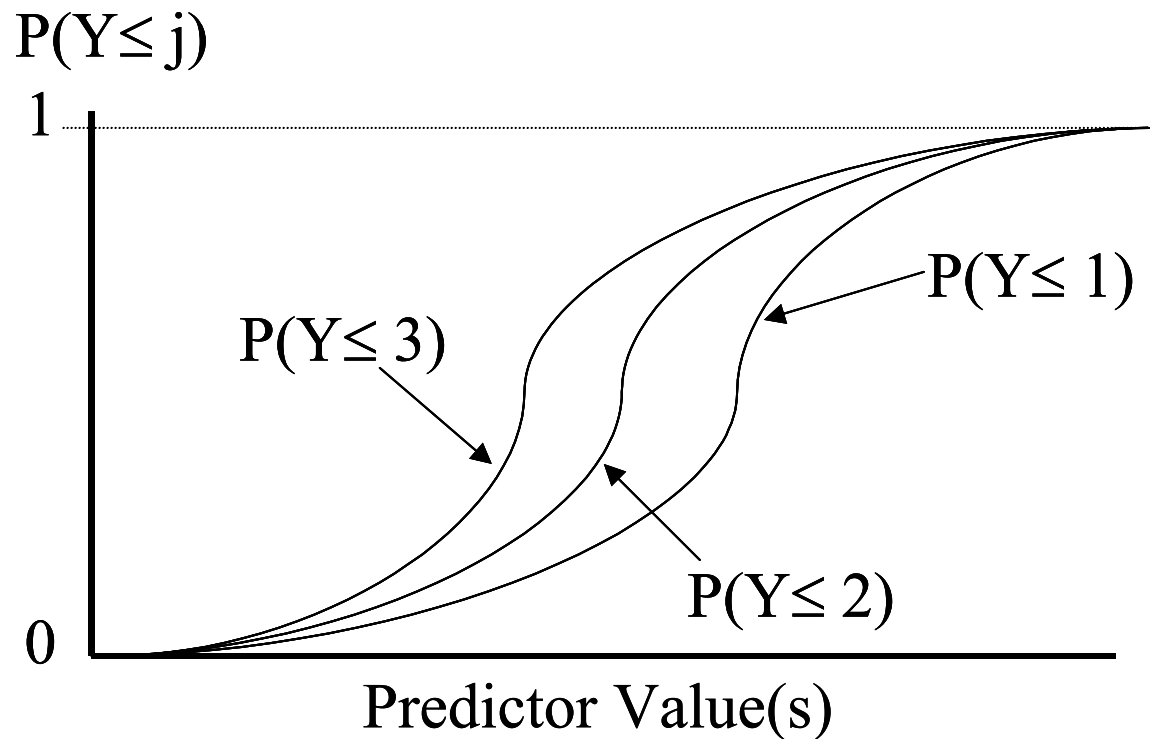




Algorithms

4 of 4

Ordinal Logistic Regression





Results

Multiple Regression

1 of 7

- The more complex the model, the better it did with both training and test datasets
- Best model incorporated transformed 4th order polynomial and interaction terms
- Problem ~ Heteroscedasticity
(*non-constant variance*)



Results

Regression Trees

2 of 7

- Program limitations for data size
 - 60,000 observation training dataset
 - 60,000 observation test dataset
- Least squares tree tested 2611 trees
- Least absolute deviation tested 172 trees



Results

Regression Trees

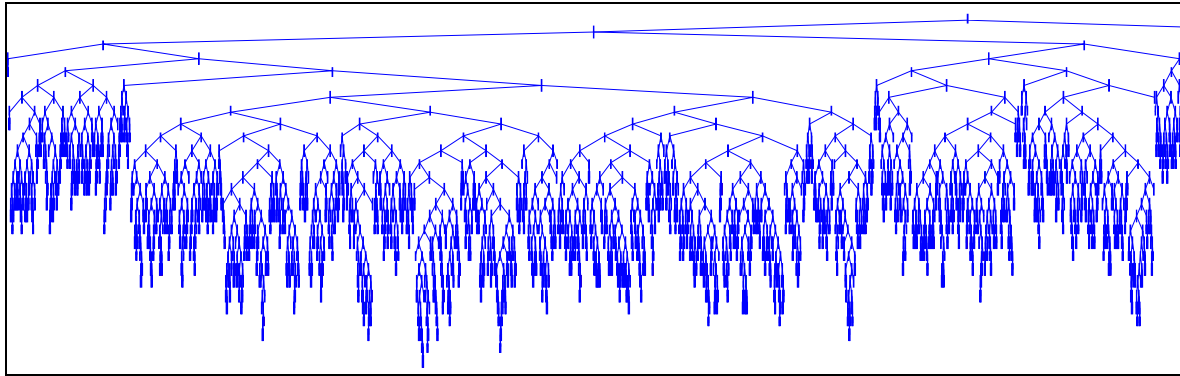
3 of 7

- Least absolute deviation regression tree was the best
 - Fewer nodes 819 vs. 1857
 - Smaller Complexity value: -1.0 vs 37.6
 - Smaller Root MSE for test set

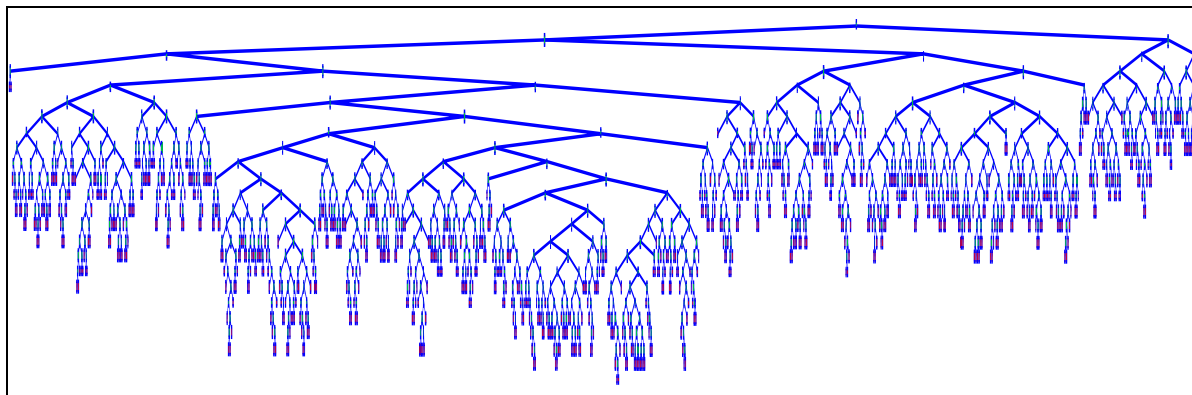
Results

Regression Trees

4 of 7



Least Squares Regression Tree



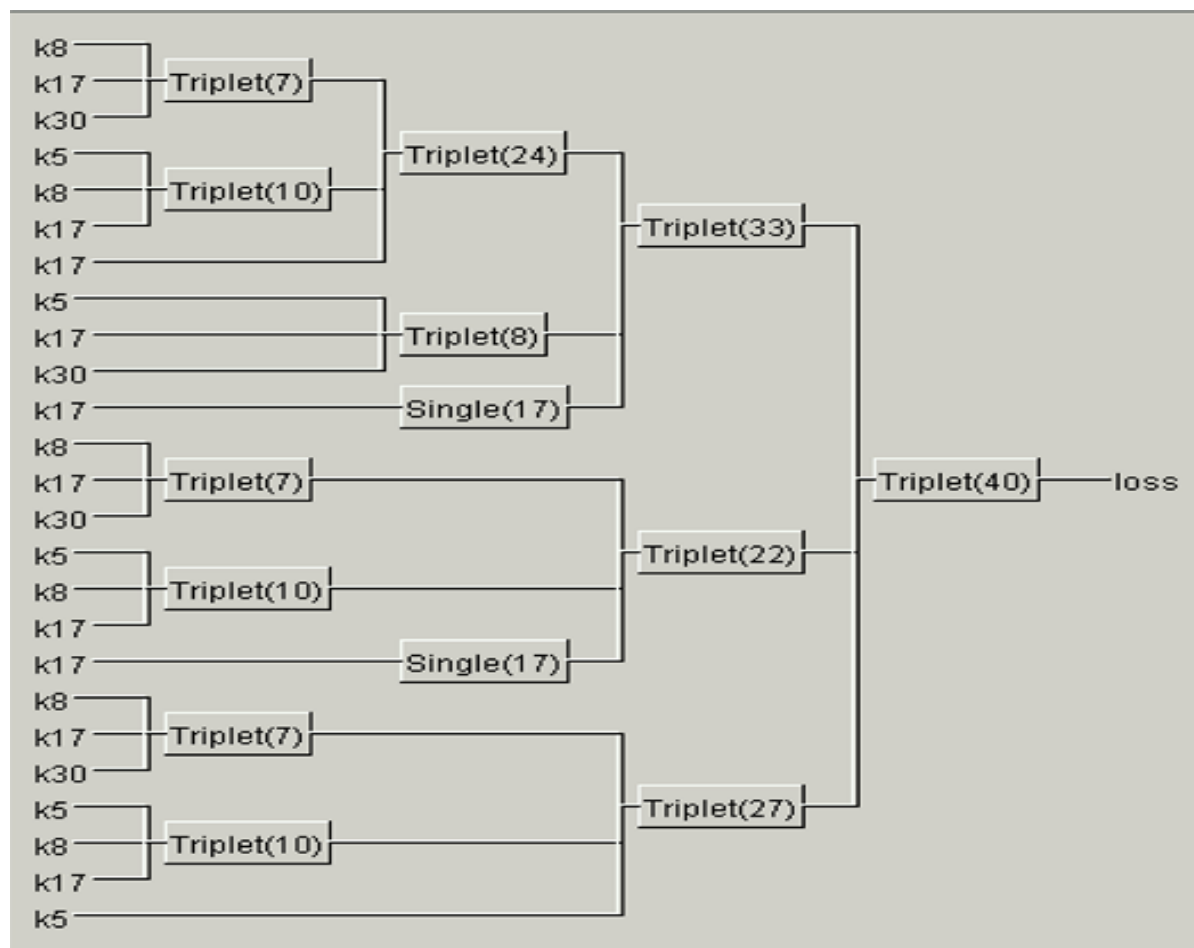
Least Absolute Deviation Regression Tree



Results

Polynomial Networks

5 of 7





Results

Ordinal Logistic Regression

6 of 7

- The more complex the model, the better it did with both training and test datasets
- Best model incorporated transformed 4th order polynomial and interaction terms



Results

Model Selection

7 of 7

Overall Model Comparison by Test Set		
<i>Model</i>	<i>RT MSE</i>	<i>VAR</i>
Multiple Regression Model 8	5.388	29.030
Logistic Regression Model 8	5.610	31.468
Polynomial Network	4.872	23.739
LAD Regression Tree	0.566	0.320

Interpretation of Results

More Complex = Better Model

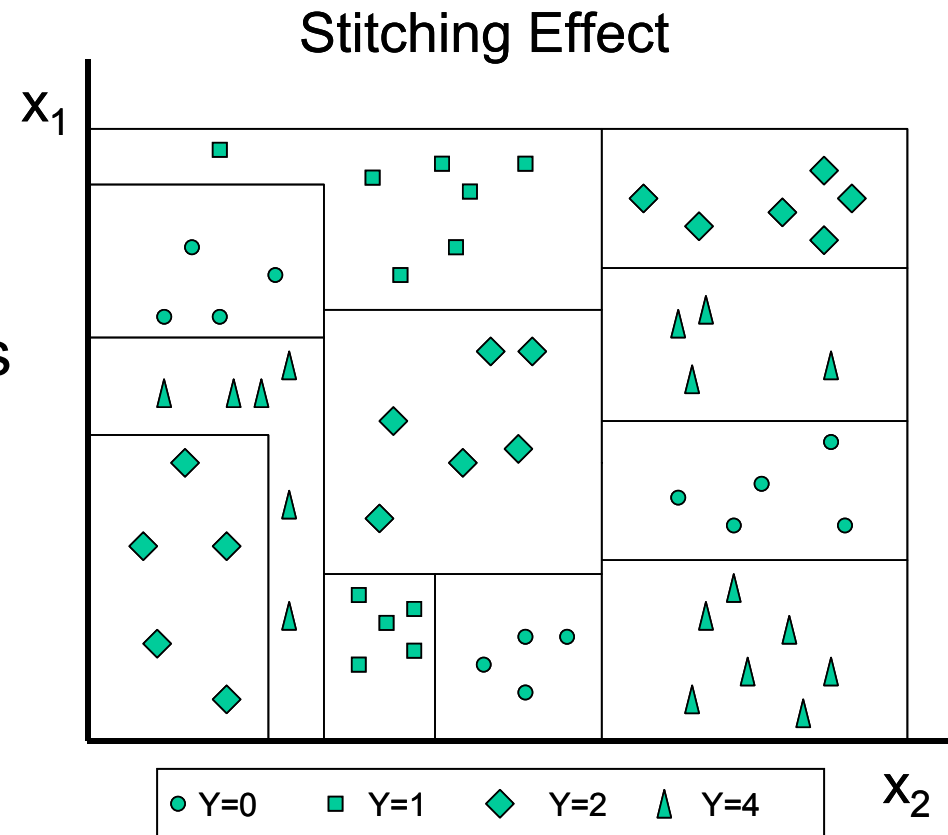


1 of 3

Dataset requires
complex parametric models

Or

Non-parametric models



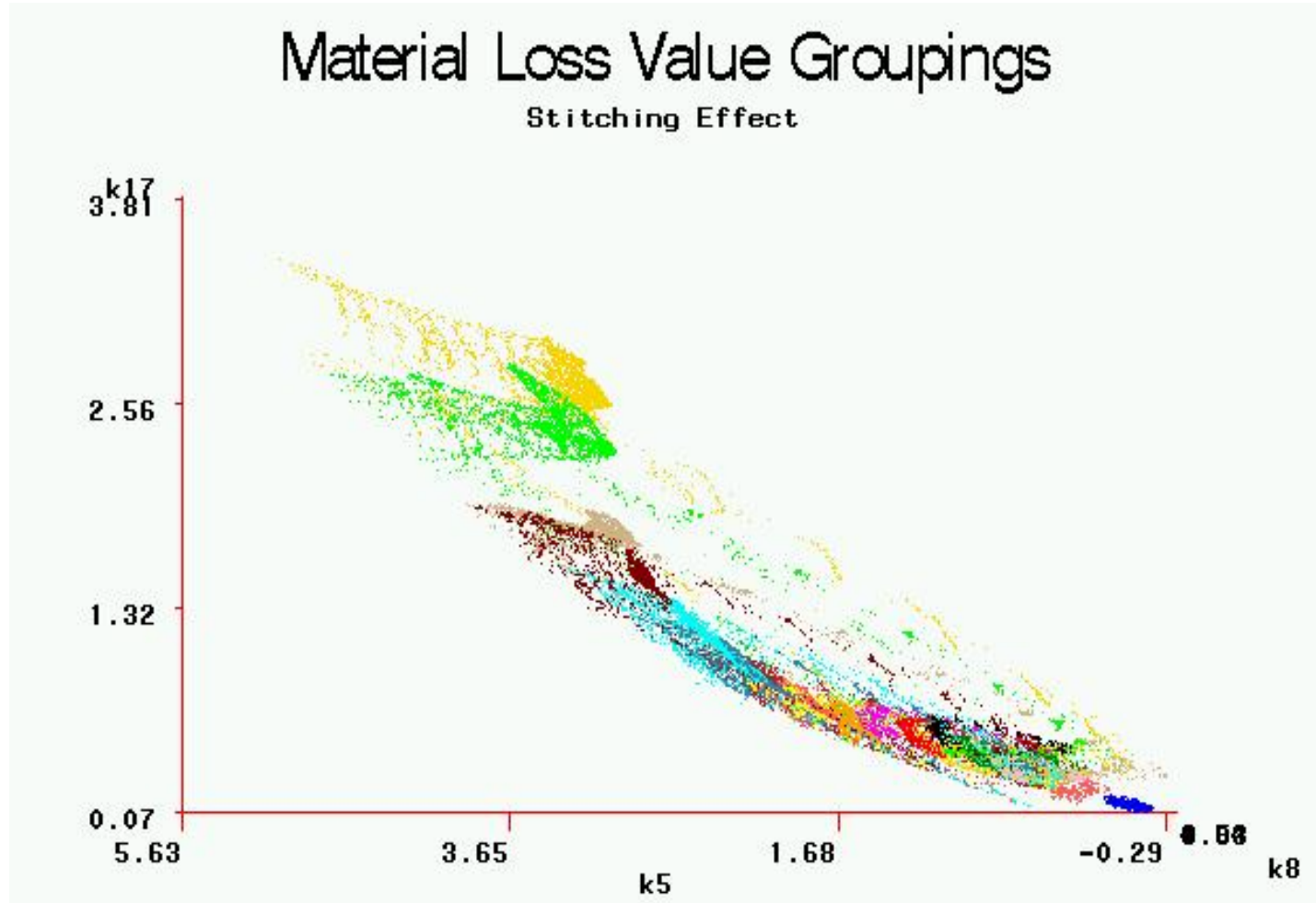
Interpretation of Results

More Complex = Better Model

2 of 3



STITCHING
EFFECT



Complexity Challenges in Eddy Current NDT Data

Interpretation of Results

Why LAD RT does well

3 of 3



LAD regression tree does well because:

- Robust in presence of heteroscedasticity
- Partitioning provides for improved accuracy
- Uses “stitching” to capture nonlinearities



Conclusions

1 of 2

Maintenance Operations

- *Showed that an algorithm can be developed to assist operators in maintenance decisions*
- *Showed how to transform and clean the eddy current data for analysis*
- *Provided a basis for choosing among competing algorithms for actual implementation*



Conclusions

2 of 2

Methodological

- *Provided a formal approach for comparing different data mining techniques on real corrosion data*
- *Showed that real data sets can produce highly complex relationships (contrast with Ockham's razor) and that models can be found to handle these complexities*
- *Demonstrated the power of tree-based methods to treat nonlinearities in the data through “stitching”, which was formerly thought to be a disadvantage*

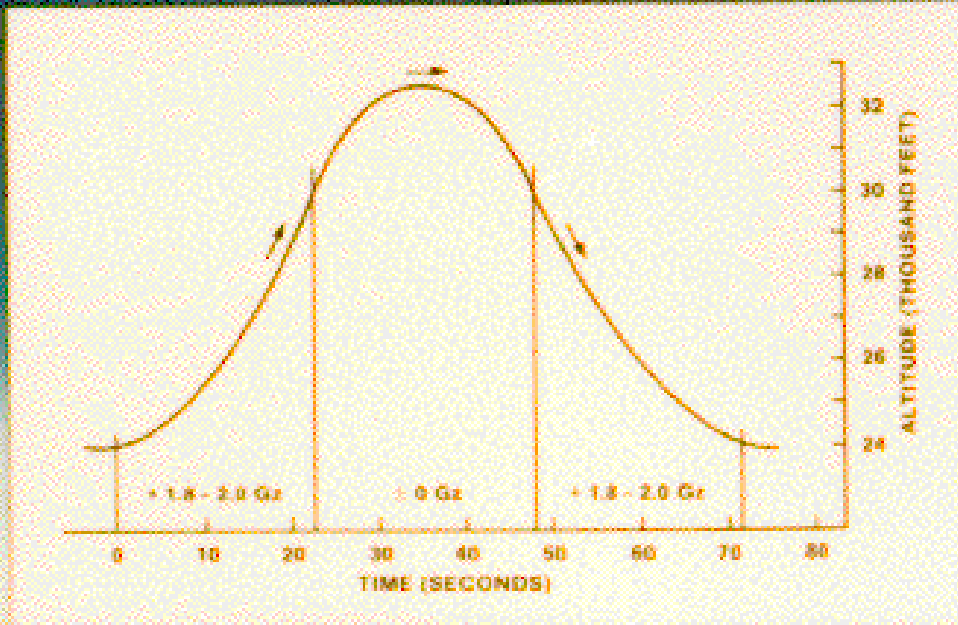


Future Research

- Classification algorithms
- If time-lapse available ~ time series analysis
- Spatial models (correlation between corrosion areas)
- Other non-parametric techniques
- Application of a “known” naturally corroded specimen as test dataset



Questions ?



NASA's "Vomit Comet"