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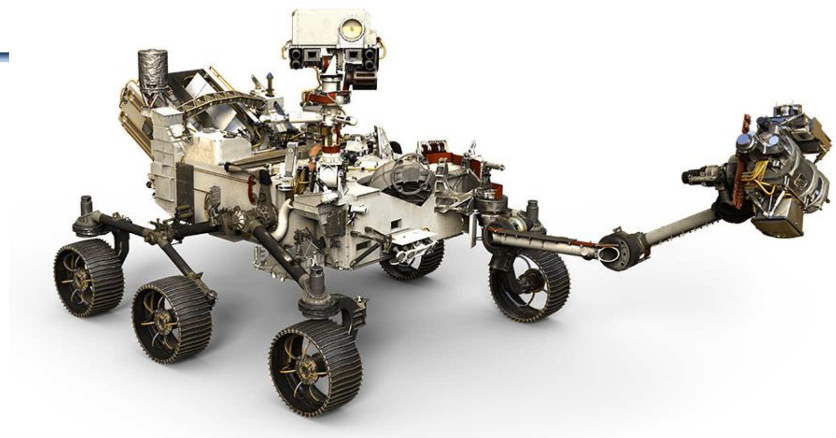
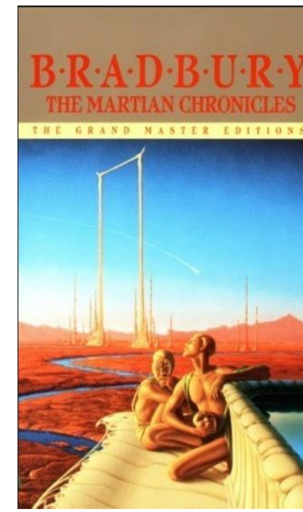


You Don’t Have to be a Rocket Scientist: JMP Martian Chronicles



October 20, 2017

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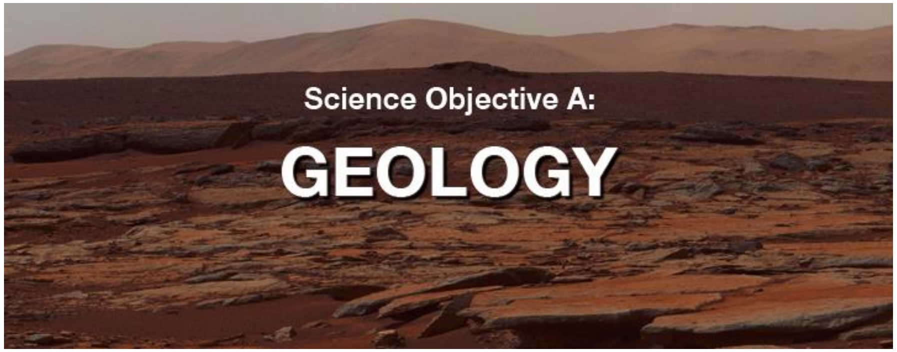
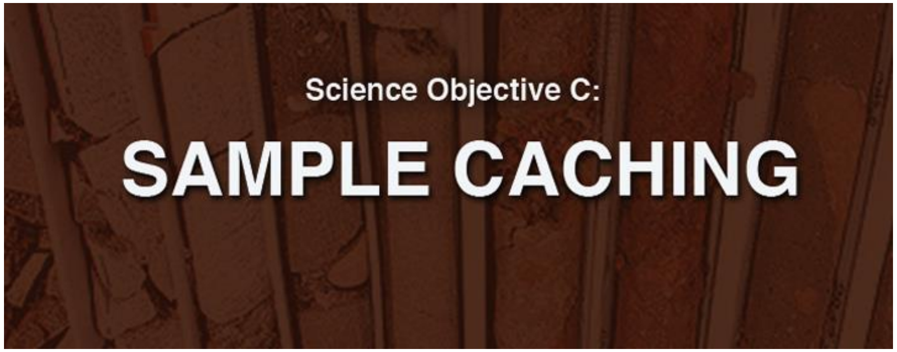
Mars 2020 Rover

- The Mars 2020 rover will robotically explore the red planet's surface for at least 1 Martian year (687 Earth days)
- Builds on success of Mars Science Laboratory's Curiosity Rover to minimize program risk





Sample Caching Subsystem

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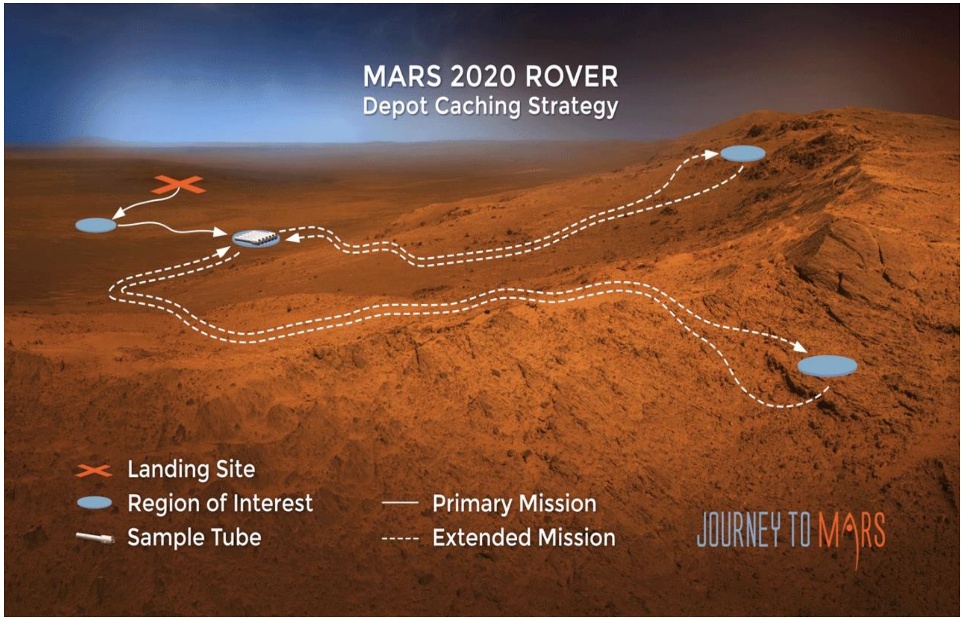

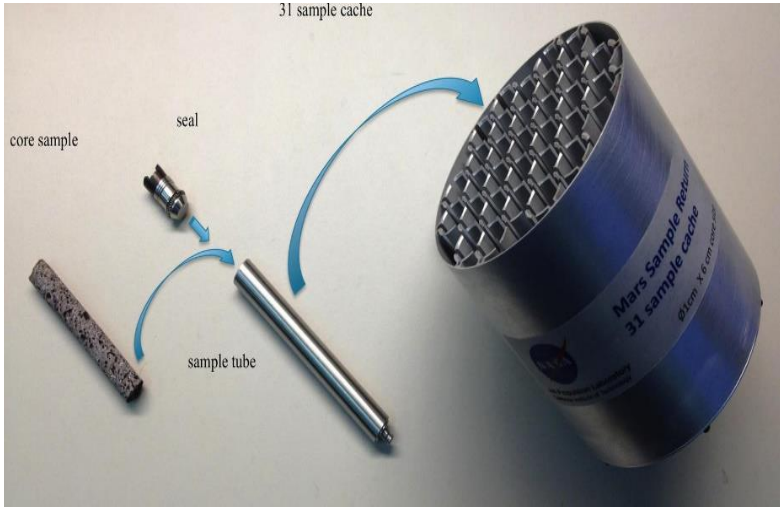

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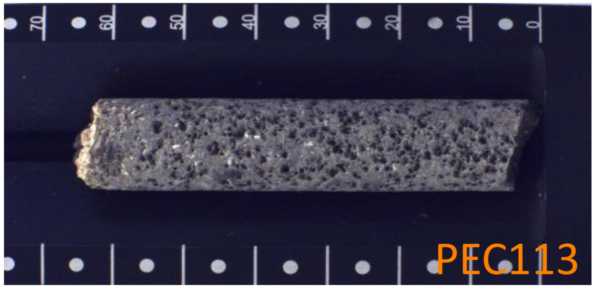
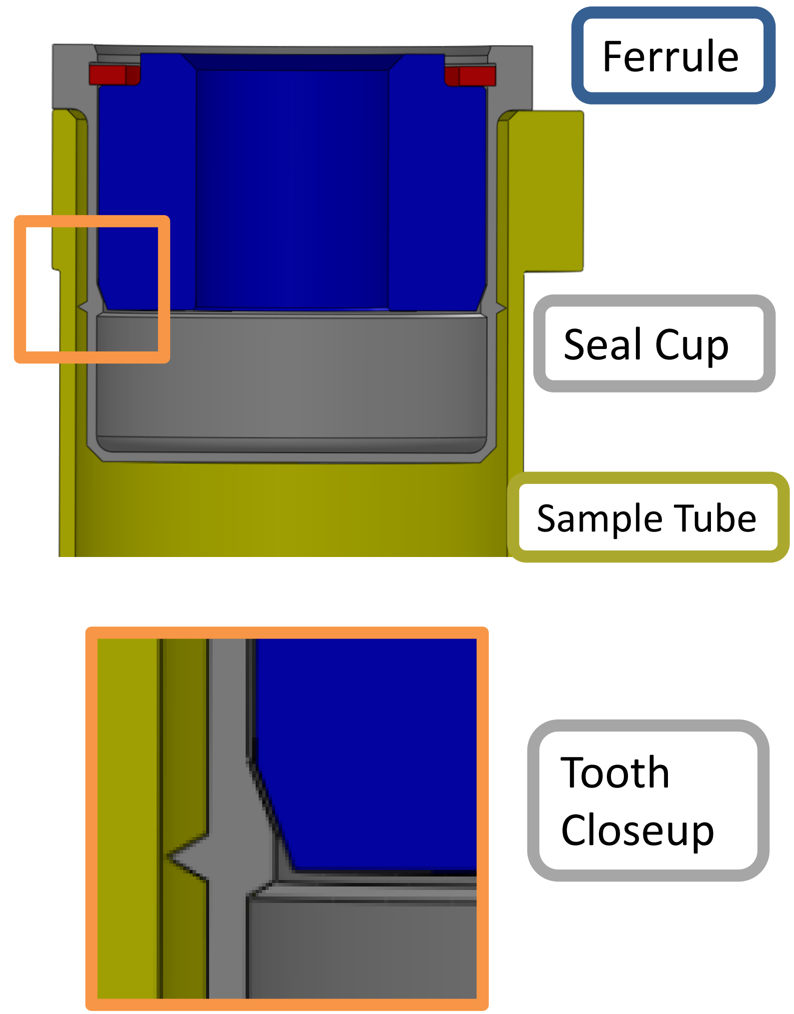
Subsystem Design

- We don’t get to control Mars!
  - Subsystem design highly informed by testing
- Key requirements:
  - Collect ~40 cores of varying sample types, based on notional distribution of Earth analog rocks
  - Core quality - Best core has a few number of large pieces
  - Samples must be “hermetically” sealed
- Measurable responses
  - Core quality
    - Mass and number of pieces to pass through sieves of 2, 5, 10 and >10 mm
    - Sample volume
  - Seal leak rate
  - Drilling Performance
    - Avg cycle sideload
    - Avg cycle percussion current
    - Avg drilling torque
    - Avg percussion power
    - Avg rate of penetration



Vignette 1.
Space Filling Designs

- Problem: Prior tests showed hermetic seal performance is highly dependent on line load, but it is not directly measurable! Line load is estimated via nonlinear FEA model
- Knew important factors from previous FEA runs
- Platforms and topics: space filling design, predictive modeling, profiler and optimization
- Methodology: Create space filling design with candidate factors, fit neural models holding back a few runs as validation,
- Results:
  - Simple neural network model captures the nonlinearities
  - First form of line load model used before sealing test to compute ideal part dimensions
  - Second form of line load model used after sealing test to estimate actual achieved line load



Vignette 1. Space Filling Design

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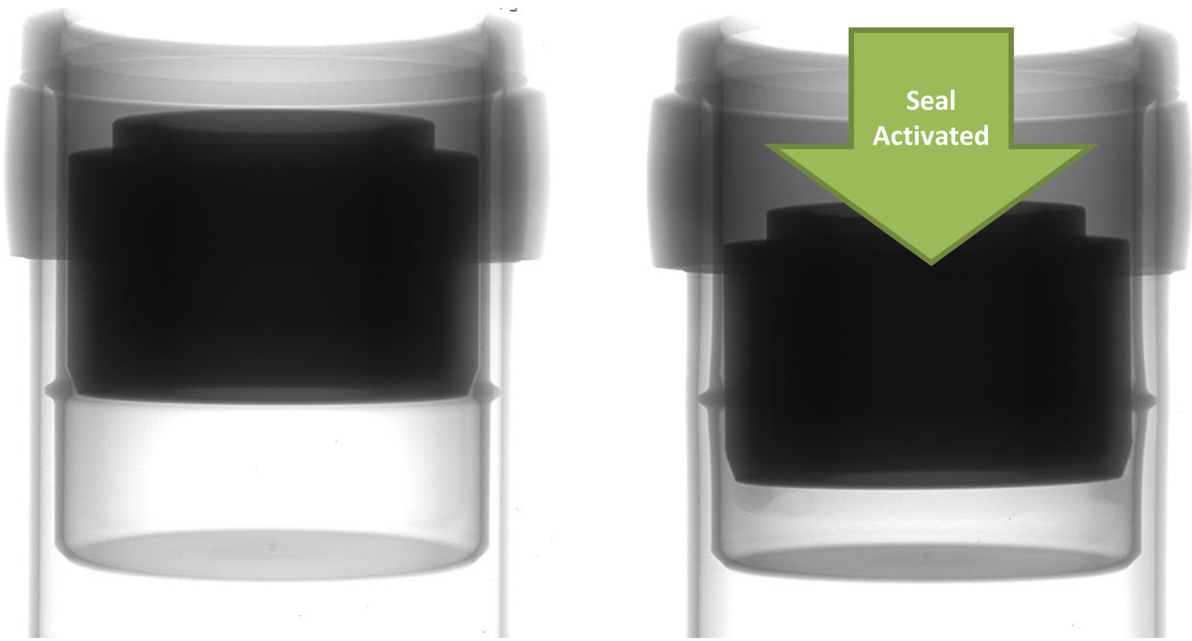
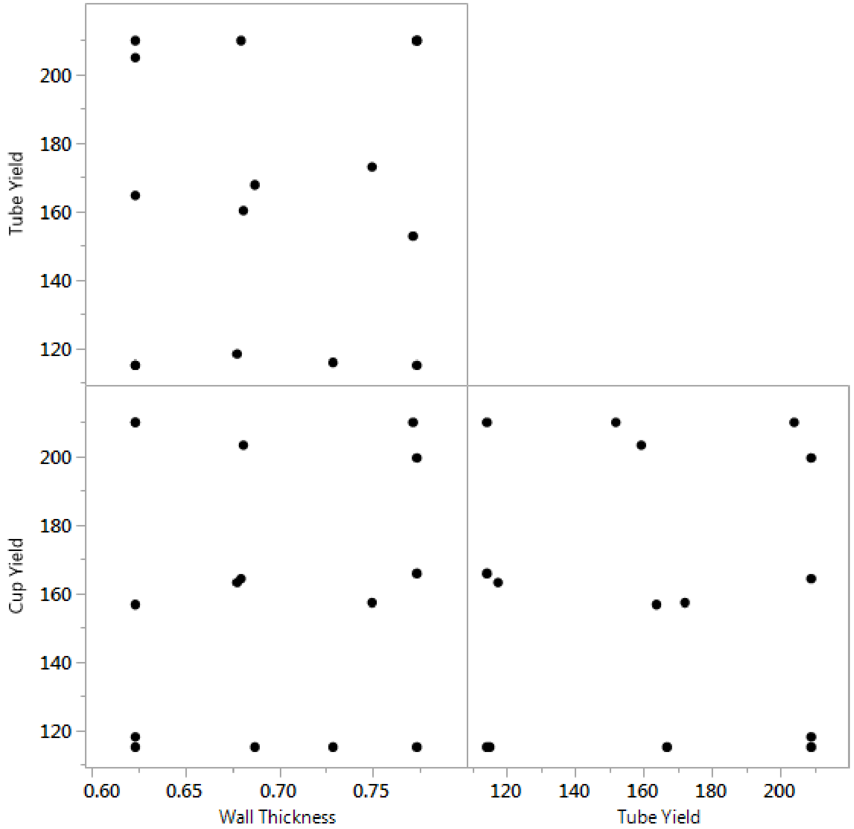


- Need 2 forms of model
  - Form 1 – given a target Line Load, what Tooth Interference do we need?
    - Line_Load = f(Tooth Interference, Wall Thickness, Tube Yield, Cup Yield)
    - This tells us how to grind the ferrule OD based on the Ramp ID
  - Form 2 – given a measured tube expansion (and other factors), what is the estimated Line Load?
    - Line_Load = f(Tube Expansion, Wall Thickness, Tube Yield, Cup Yield)
    - Used after seal is activated to estimate actual Line Load

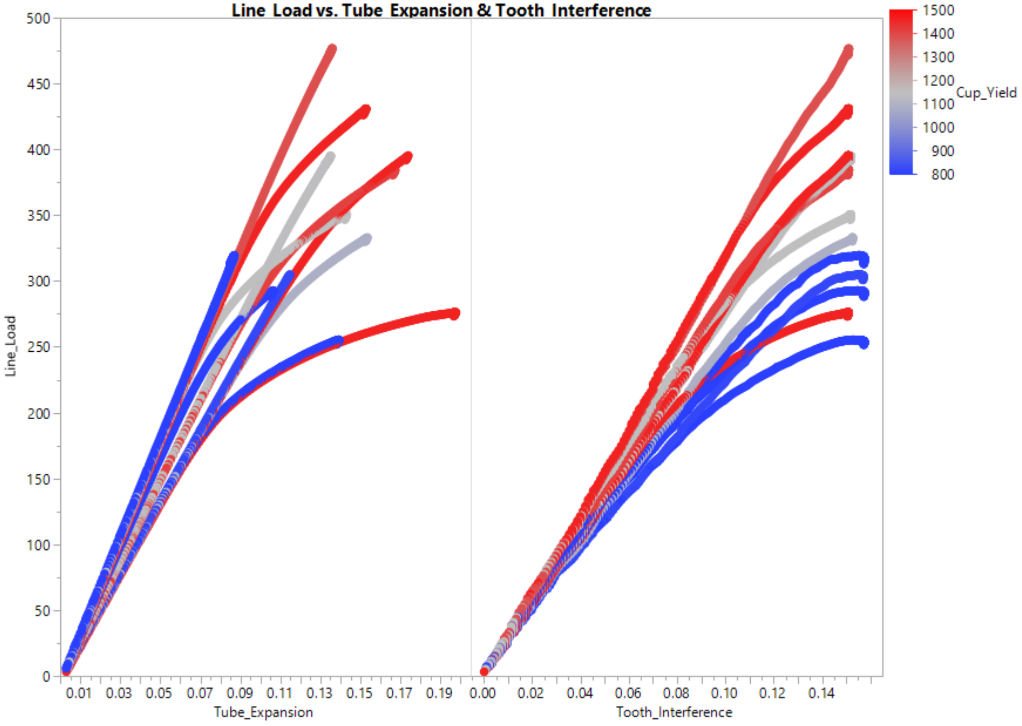
Vignette 1.
Space Filling Design

- Space filling design with 3 factors
- 15 runs chosen as a good balance between filling the space and not overwhelming the FEA analyst



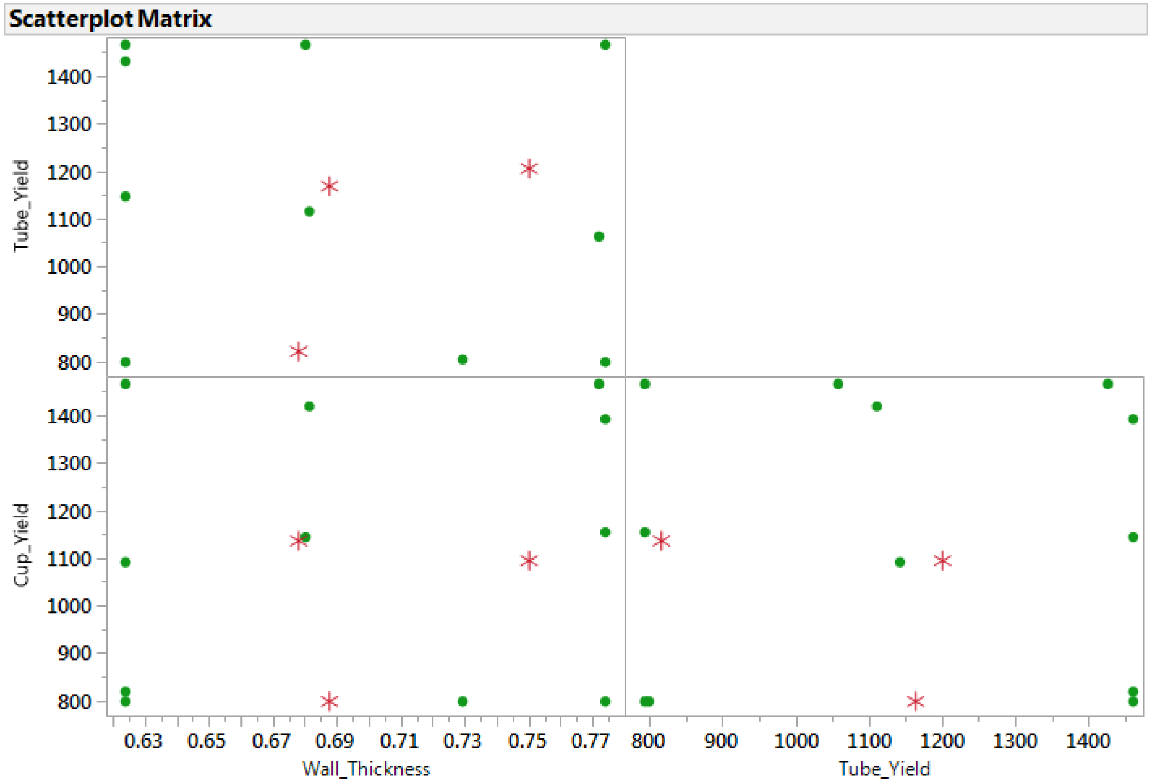
Vignette 1.
Space Filling Design

- Single FEA run gives 100's of data points for Tooth Interference and Tube Expansion



Vignette 1. Space Filling Design

- 3 runs randomly selected to hold back for validation



Vignette 1. Space Filling Design

- Use Profiler and Desirability to find Tooth Interference required to achieve desired Line Load
- Likewise, use Profiler after test is performed to estimate actual Line Load from measured Tube Expansion

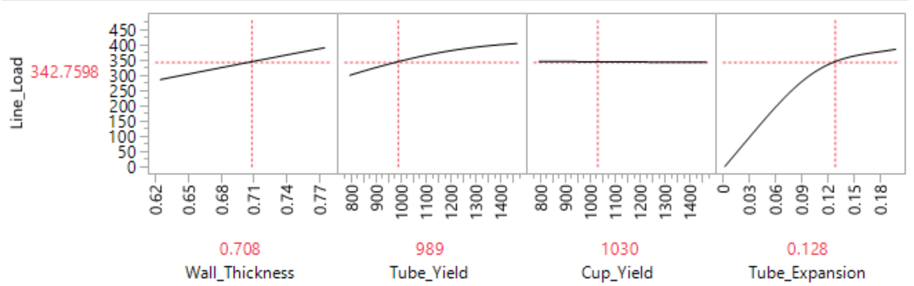
Training — Line_Load

Measures	Value
RSquare	0.9998587
RMSE	1.4252988
Mean Abs Dev	1.1331251
-LogLikelihood	7800.8348
SSE	8936.4661
Sum Freq	4399

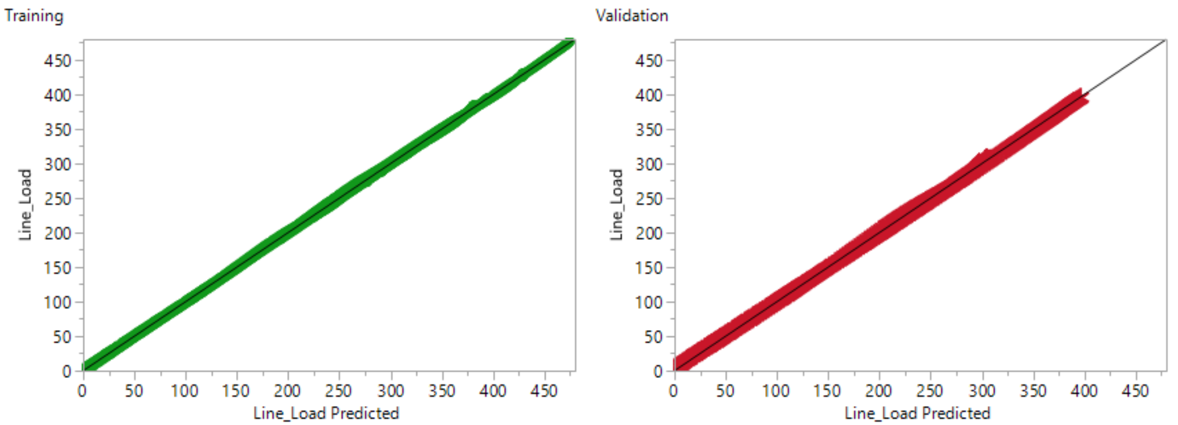
Validation — Line_Load

Measures	Value
RSquare	0.9997298
RMSE	1.8032011
Mean Abs Dev	1.4909835
-LogLikelihood	2161.1482
SSE	3498.651
Sum Freq	1076

Prediction Profiler



Actual by Predicted Plot



Vignette 2.
Complex Distribution

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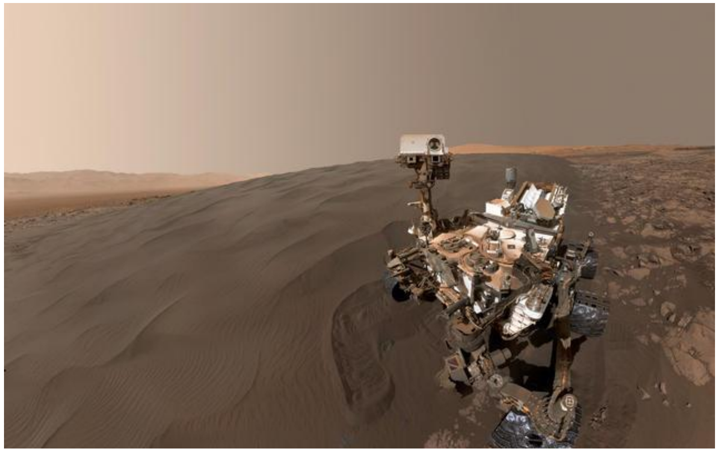
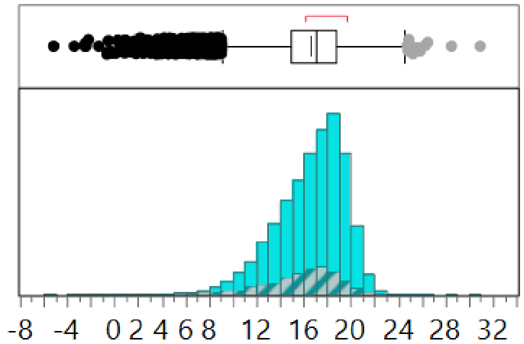
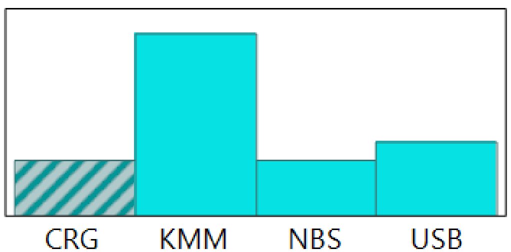
- Problem: What is the overall distribution for Core Total Mass given we have test data for the 4 types of rocks but at much different percentages than expected for 2020 missions?
- Platforms and topics: data cleaning, data visualization, filtering, fitting non-normal distributions, simulation
- Methodology: For each rock type, determine the best distribution and parameters, generate 100,000 * (expected percent on Mars) observations, concatenate all 4 random variates, fit all 100,000 observations to a new distribution
- Results:
  - Log Generalized Gamma is best fit
  - Dynamic exploration with profilers
  - Quantify risk of having less than 15g



Vignette 2. Complex Distribution



RockCode



Frequencies

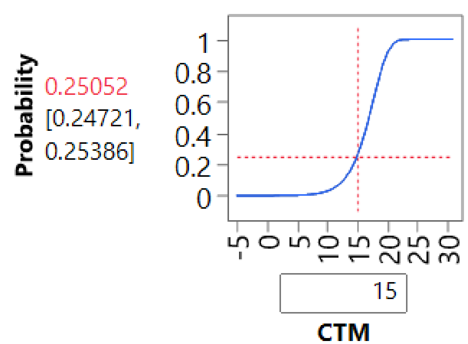
Level	Count	Prob
CRG	15000	0.15000
KMM	50000	0.50000
NBS	15000	0.15000
USB	20000	0.20000
Total	100000	1.00000

N Missing 0
4 Levels

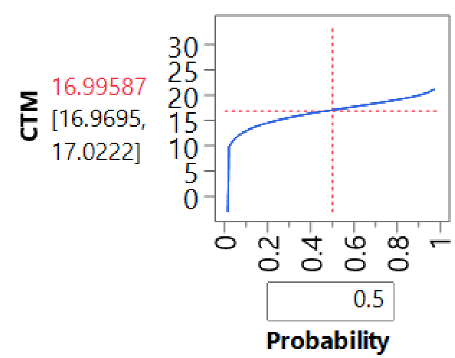
Model Comparisons

Distribution	AICc
Log Generalized Gamma	483924.04
SEV	484454.23
Logistic	494677.33
Normal	495485.46
LEV	538932.46

Distribution Profiler



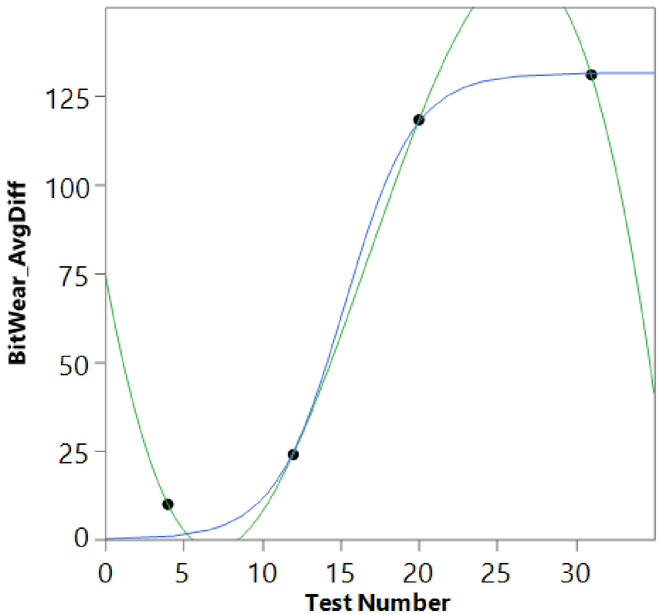
Quantile Profiler



Vignette 3.
Modelling Bit Wear

- Problem: How can we model the impact of bit wear on drill performance metrics? Is there a surrogate measure for bit wear?
- Platforms and topics: data visualization, fit curve, nonlinear modelling, column switcher, multivariate, fit model stepwise
- Methodology: Measure bit wear 4 times over a series of 30 tests, fit candidate nonlinear models, create new control variable as bit wear over time, run regression models
- Results:
  - Bit wear approximated well by Logistic 3Parameter Sigmoid Curve
  - Makes sense from physics of failure/degradation models
  - Highly correlated with Time in USB rocks
  - Useful control variable for many of the responses

Vignette 3. Modelling Bit Wear



Prediction Model

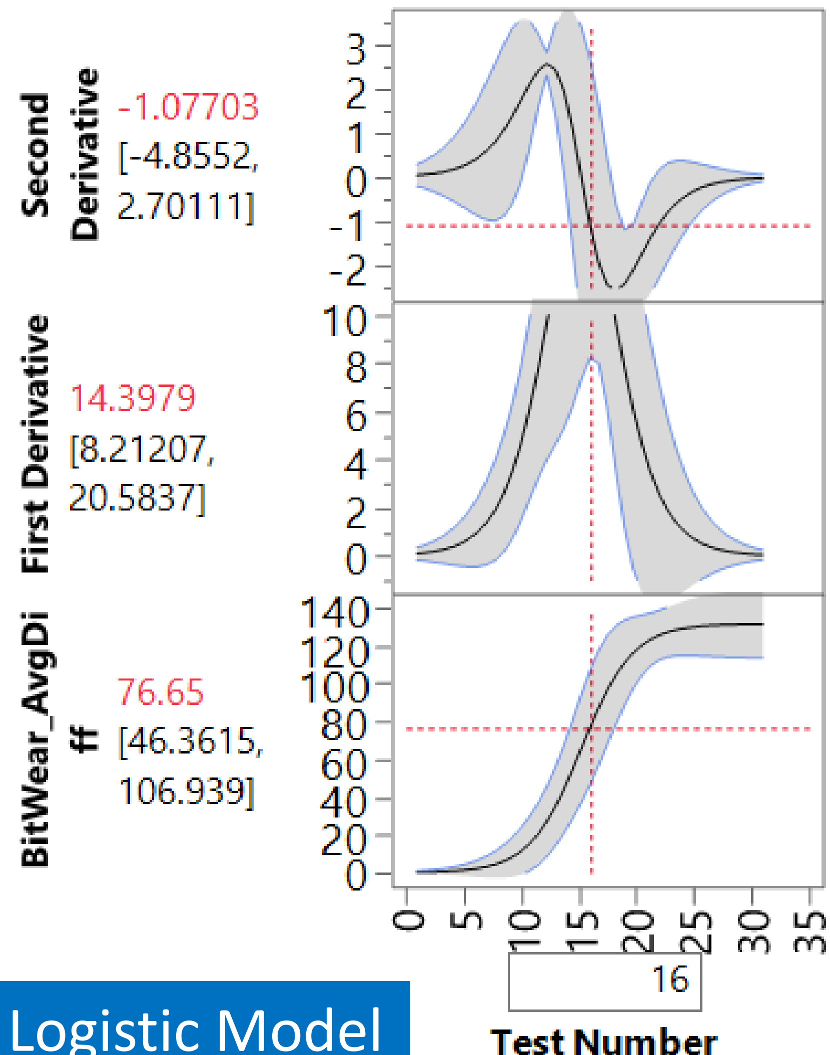
$$\frac{c}{\left(1 + \mathrm{Exp}\left(-a \cdot \left(\text{Test Number} - b\right)\right)\right)}$$

a = Growth Rate

b = Inflection Point

c = Asymptote

Prediction Profiler



3 Parameter Logistic Model

Vignette 3.
Modelling Bit Wear

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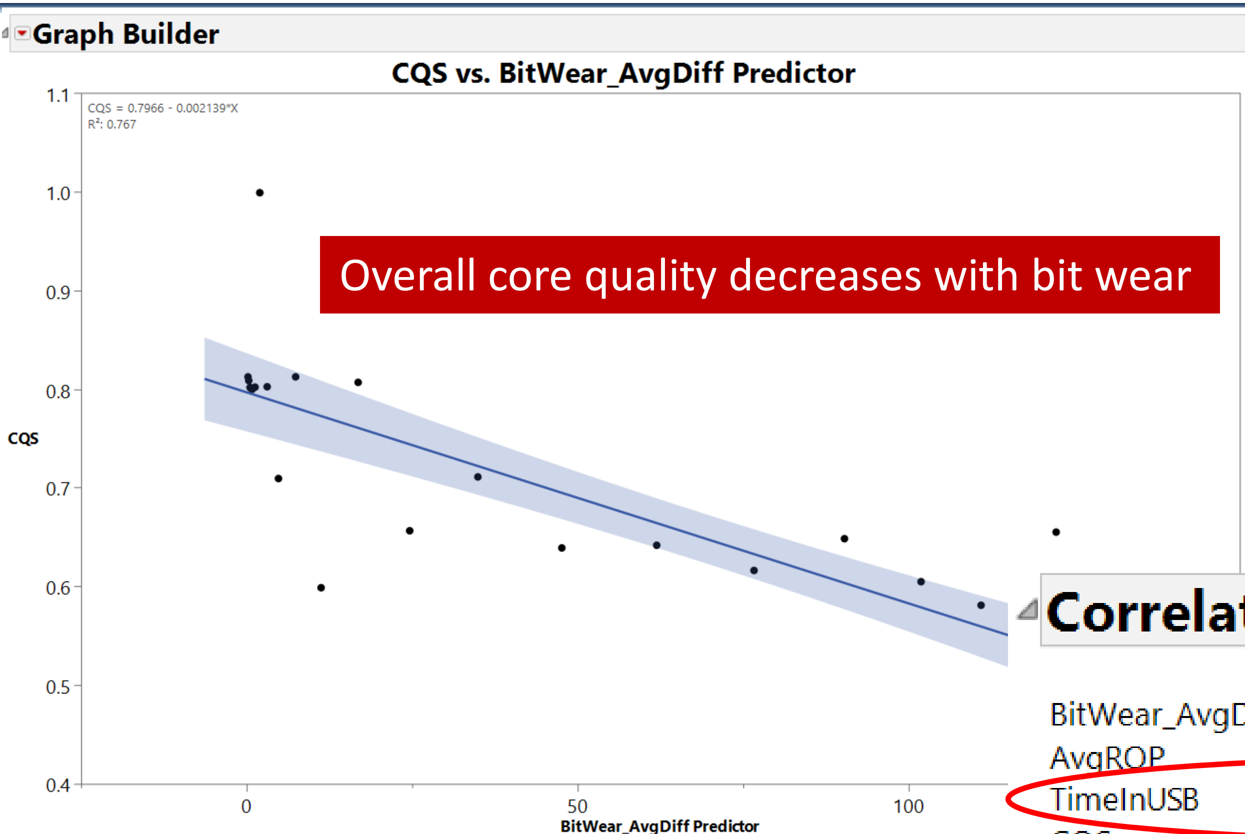

Correlations

	BitWear_AvgDiff Predictor
BitWear_AvgDiff Predictor	1.0000
AvgROP	-0.5094
TimeInUSB	0.9684
CQS	-0.8756
CoreTotalMass	-0.2533
CoreVolRatio	0.7149
TPEL_error	0.6313
CoreMassGT10mm	-0.3997
CoreNumPieces10_above	0.8828
CoreMassPerPiece_above_10mm	-0.8112
CoreVol_GT_10mm	-0.3997
CoreNumPieces	0.6037

Vignette 3.
Modelling Bit Wear

Stepwise Fit for CoreTotalMass

Stepwise Regression Control

Stopping Rule: Minimum BIC

Direction: Forward

Rules: Combine

Enter All | Make Model | Remove All | Run Model

Go | Stop | Step

1 rows not used due to excluded rows or missing values.

SSE	DFE	RMSE	RSquare	RSquare Adj	Cp	p	AICc	BIC
14.395064	24	0.7744639	0.6662	0.5967	12.812759	6	82.19786	86.91533

Current Estimates

Lock	Entered	Parameter	Estimate	nDF	SS	"F Ratio"	"Prob>F"
☑	☑	Intercept	153.987214	1	0	0.000	1
☐	☑	BitWear_AvgDiff Predictor	-0.3984135	3	11.22554	6.239	0.00276
☐	☑	FixtureName{EDT-PEC}	79.1205223	2	13.97101	11.647	0.00029
☐	☐	DrilSpindleRate	0	1	0.034134	0.055	0.8172
☐	☐	AvgCycleWOB	0	1	1.22575	2.141	0.15696
☐	☐	Bits_ToothRakeAngle	0	0	0	.	.
☐	☑	DrillingOrientation	-4842.4669	2	10.07633	8.400	0.00172
☐	☐	AbsPercLevel	0	1	0.738844	1.244	0.27615
☐	☑	(BitWear_AvgDiff Predictor-66.8819)*FixtureName{EDT-PEC}	-1.2538818	1	6.88123	11.473	0.00243
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(DrilSpindleRate-197.933)	0	2	0.096273	0.074	0.92884
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(AvgCycleWOB-79.9826)	0	2	1.9251	1.698	0.20614
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(Bits_ToothRakeAngle--20)	0	0	0	.	.
☐	☑	(BitWear_AvgDiff Predictor-66.8819)*(DrillingOrientation-0.01718)	75.7241276	1	9.366442	15.616	0.0006
☐	☐	(BitWear_AvgDiff Predictor-66.8819)*(AbsPercLevel-32.8331)	0	2	1.526238	1.305	0.29146
☐	☐	FixtureName{EDT-PEC}*(DrilSpindleRate-197.933)	0	0	0	.	.

Summary

- High priority Mars 2020 program is experimenting to accurately characterize and optimize coring performance
- JMP has enabled JPL engineers to quickly discover relationships with graphical displays and use advanced statistical methods to accurately model complex behavior across a variety of vignettes
- JMP efficiency allows team to focus more on technical challenges rather than data wrangling
- *"I would like to die on Mars—just not on impact"* Elon Musk

Questions