eastec®

MAY 14-16, 2019

EASTERN STATES EXPOSITION
WEST SPRINGFIELD, MA
easteconline.com

sme AMT THE ASSOCIATION FOR MANUFACTURING TECHNOLOGY

Official Media Partner

sme MEDIA | Manufacturing ENGINEERING. SMART manufacturing

Machine learning classification for tool life modeling using production shop-floor data

Jaydeep Karandikar
Lead Engineer
GE Research
Niskayuna, NY
USA

Peng Li
Senior Principal Scientist
GE Research
Niskayuna, NY
USA

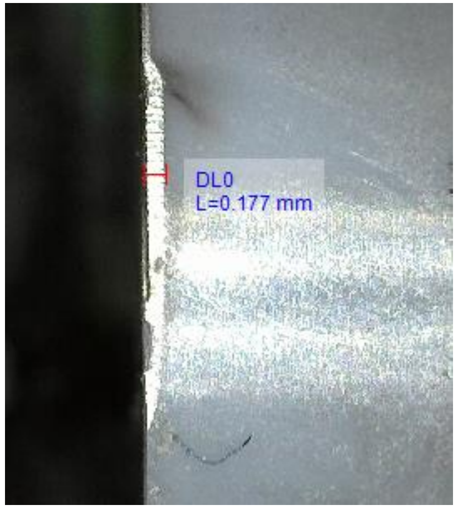
eastec®

Motivation

- Tool life is the most important limitation to machining productivity

- Tool life defined as time required for the tool to reach a pre-determine wear level

- Tool life in machining difficult to model and predict:
    - large number of influencing variables
    - stochastic/tool-to-tool performance variation



Flank wear on cutting insert

Motivation

- Empirical model – example: Taylor-type tool life model

$$v^p f^q T = C$$

v - cutting speed
f - feed rate
T - tool life
C - dimensionless constant

- Physics-based model – example: Usui's wear model

$$\frac{dw}{dt} = A\sigma_n v_{rel} e^{-\frac{B}{T}}$$

w – wear rate
σ_n- contact pressure
v_{rel} - relative velocity
T – absolute temperature
A, B – model constants

- Models require tool wear experiments to calibrate model coefficients
- Expensive and time-consuming for large number of tool grade – material combinations

Motivation

Idea:

- Consider production parts as tool wear experiments
- Model and predict tool life based on the data collected from the shop floor

Challenge:

- Wear data observed when insert changed in production
- Single data point on tool wear vs cut time curve – time for tool to reach pre-determined wear level not measured

Motivation

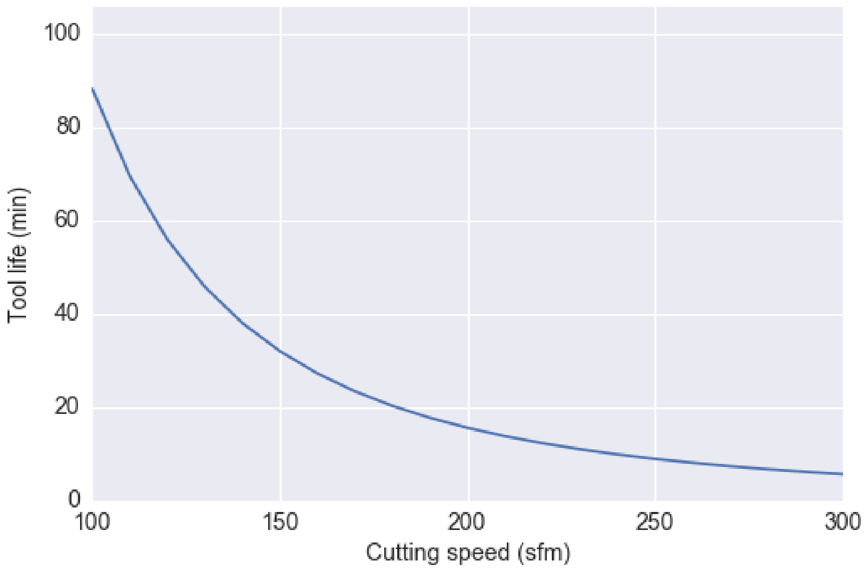
Solution:

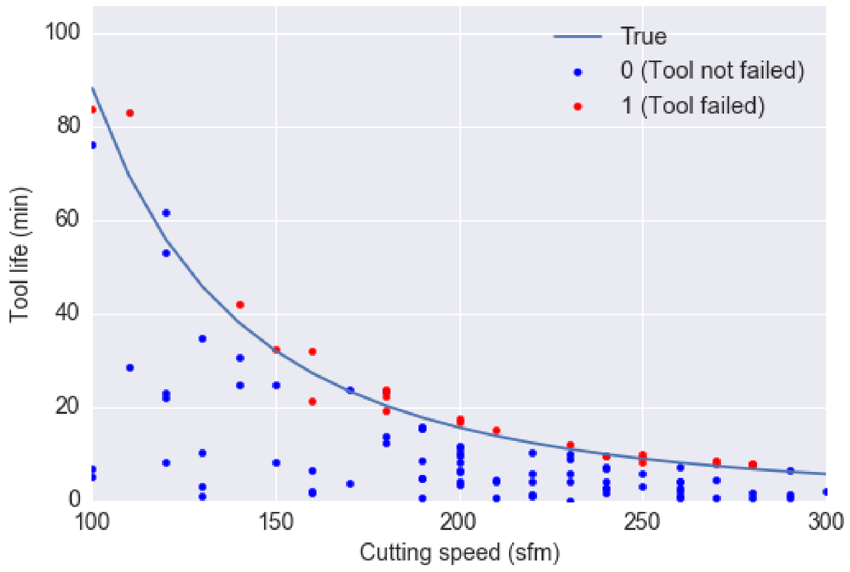
- Tool life modeling as a classification problem (as opposed to regression) – use machine learning methods for classifying tool life
  - class 0 : tool not failed (wear less than the threshold value)
  - class 1: tool failed (wear greater than the threshold value)

- Tool life – decision boundary separating the two classes as a function on input variables (cut time, and cutting speed)

Numerical Simulation

- Assume ‘true’ tool life curve as a function of cutting speed
- Generate random samples from the ‘true’ tool life curve
  - Class 0 – sample time < ‘true’ tool life value
  - Class 1 – sample time > than ‘true’ tool life value
- Add uncertainty to the samples – non-separable data





Logistic classification

- Logistic classification - probability of an event given input data using the sigmoid function

$$p(x) = \frac{1}{1 + e^{-g(x)}} = \frac{e^{g(x)}}{1 + e^{g(x)}}$$

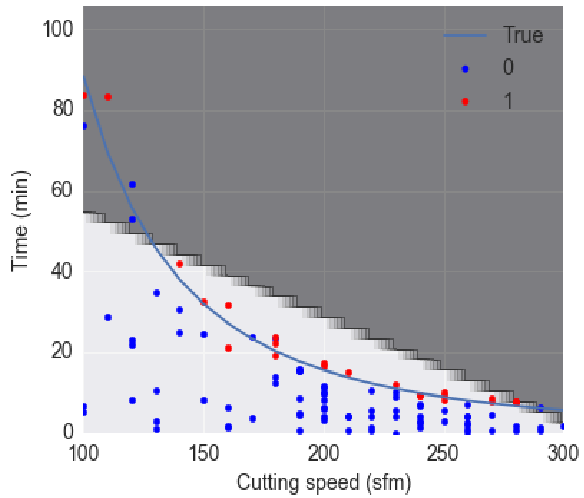
$$g(x) = a + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n$$

$p(x)$: probability of the event
$g(x)$: linear model of k input variables, x_1, x_2, … x_k

- Regularization factor C : small value denotes stronger regularization eastec®

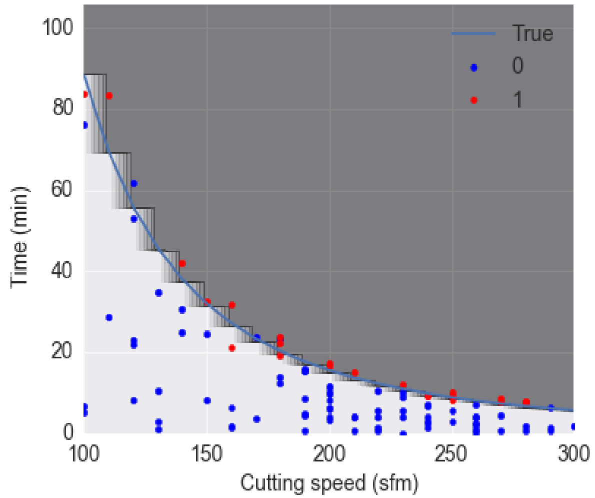
Results - Logistic Classification

- Logistic - linear classifier
- Poor accuracy – cannot capture non-linear behavior of tool life as a function of cutting speed



Tool life boundary using logistic classification

- Non-linear classification enabled by log transformation of inputs – cut time, and tool life



Tool life boundary using logistic classification using log-transformation of inputs

	n = 25	n = 50	n = 100	n = 500
Logistic log-transform	0.842	0.860	0.874	0.880

Support Vector Machine (SVM) classification

- Support Vector Machines (SVM) – hyperplane (or line in 2D) to maximize margin between classes

- SVM kernels:

Radial Basis Function (RBF)	$K(x, z) = exp(-\gamma \|\|x - z\|\|^2)$
Polynomial (Poly)	$K(x, z) = (\gamma(x^T z) + c)^d$

K : kernel function
x, z : vectors in input space
c : model coefficient
d : order of the polynomial
γ : kernel parameter

- Regularization factor *C* : penalty factor for misclassification for non-separable data

Results SVM RBF

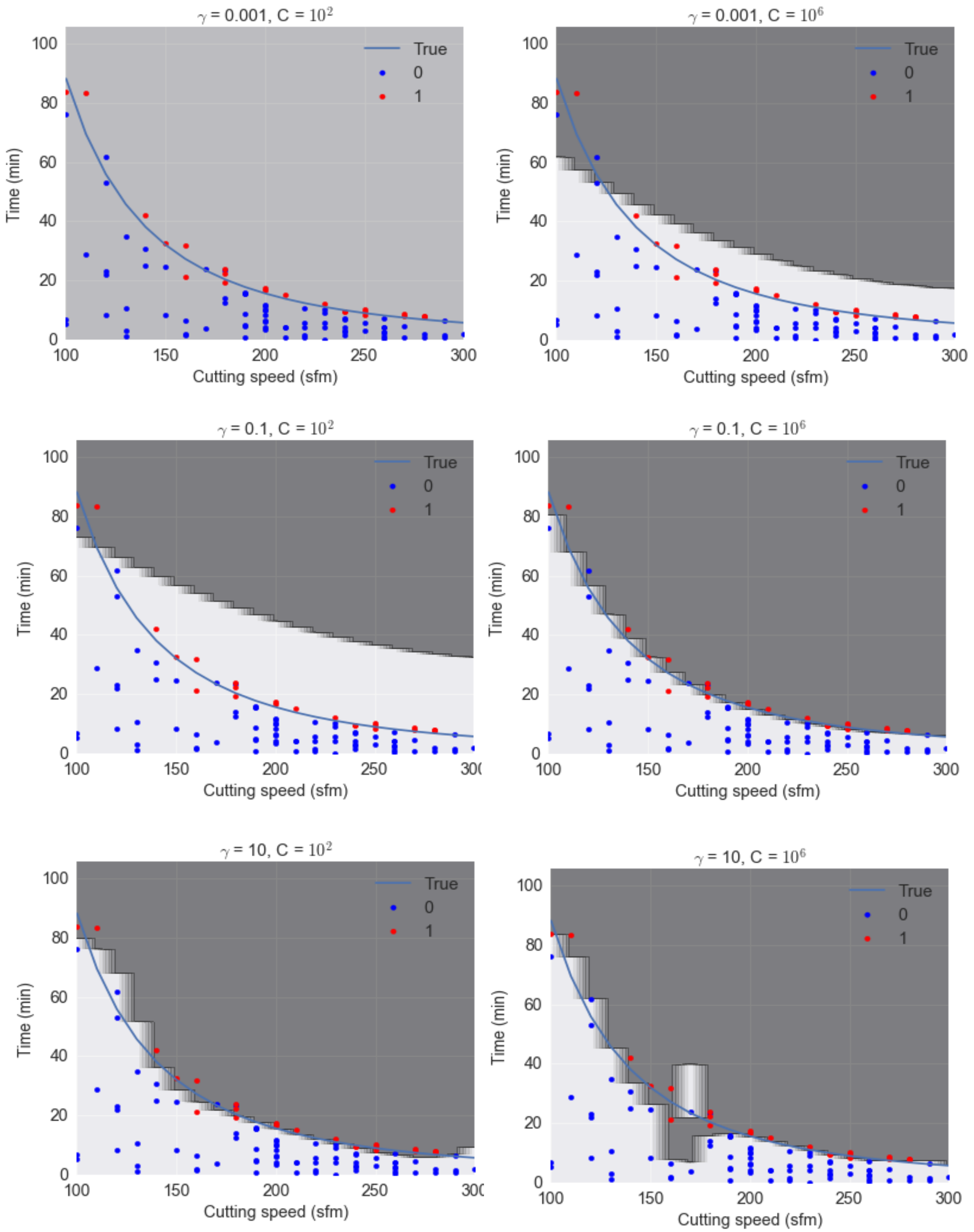
- Tune kernel parameter γ and regularization factor C to balance trade-off between over-fitting and model simplicity

γ – influence of single training data point

small γ – constrained model
large γ – overfit data and model noise

C – misclassification penalty

Small C – maximize margin – linear model
Large C – high penalty for misclassification – overfit data



Influence of (C, γ) on SVM RBF classification

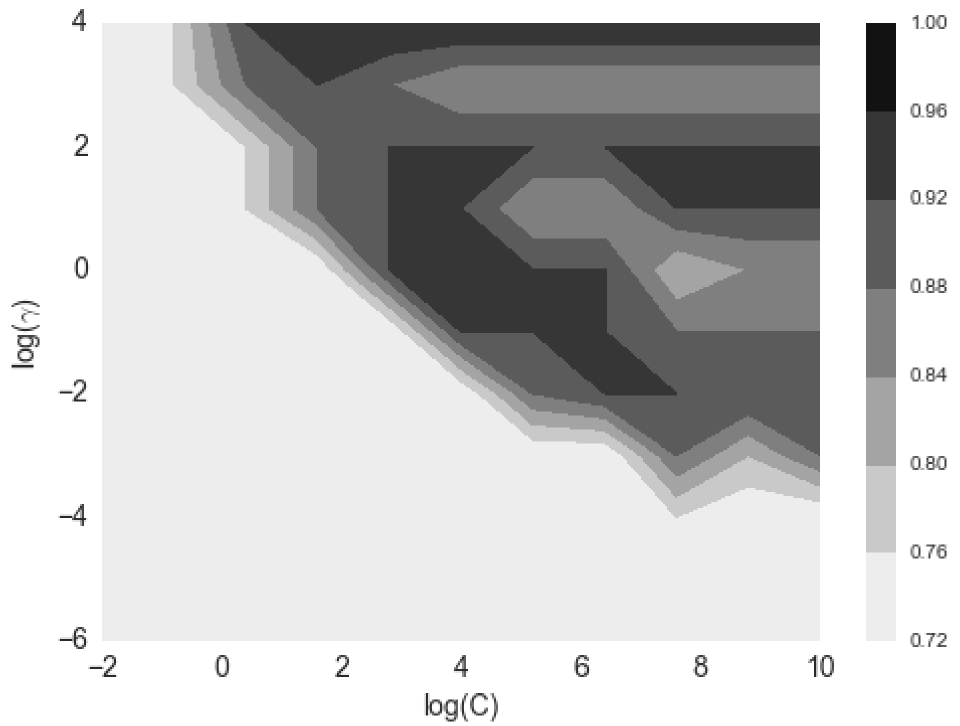
Results SVM RBF

- Grid search for optimal γ and C selection to maximize accuracy

γ = 0.1
$C = 1\times10^6$

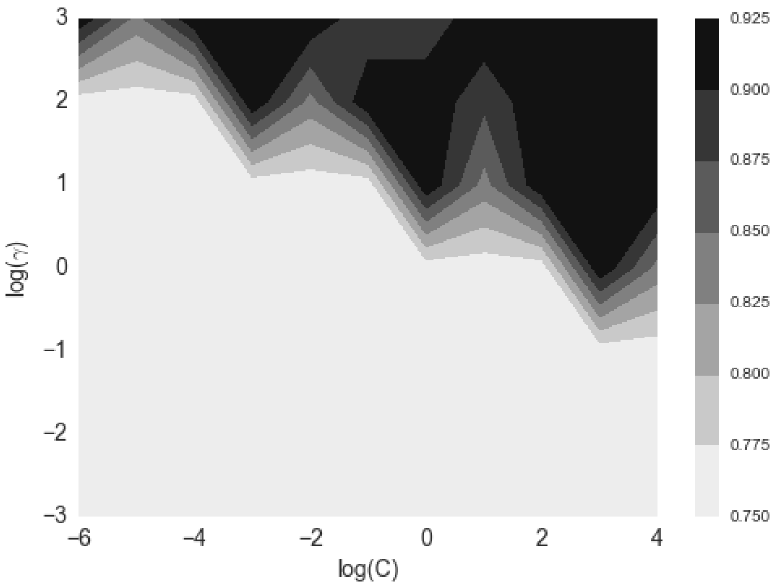
- Monte-Carlo simulation to check accuracy of SVM radial basis function model as a function of input parameters

- Model accuracy increases as a function of input points – converges to max. possible value 0.88 at 500 points



	n = 25	n = 50	n = 100	n = 500
RBF SVM	0.828	0.850	0.861	0.876

Results SVM Poly

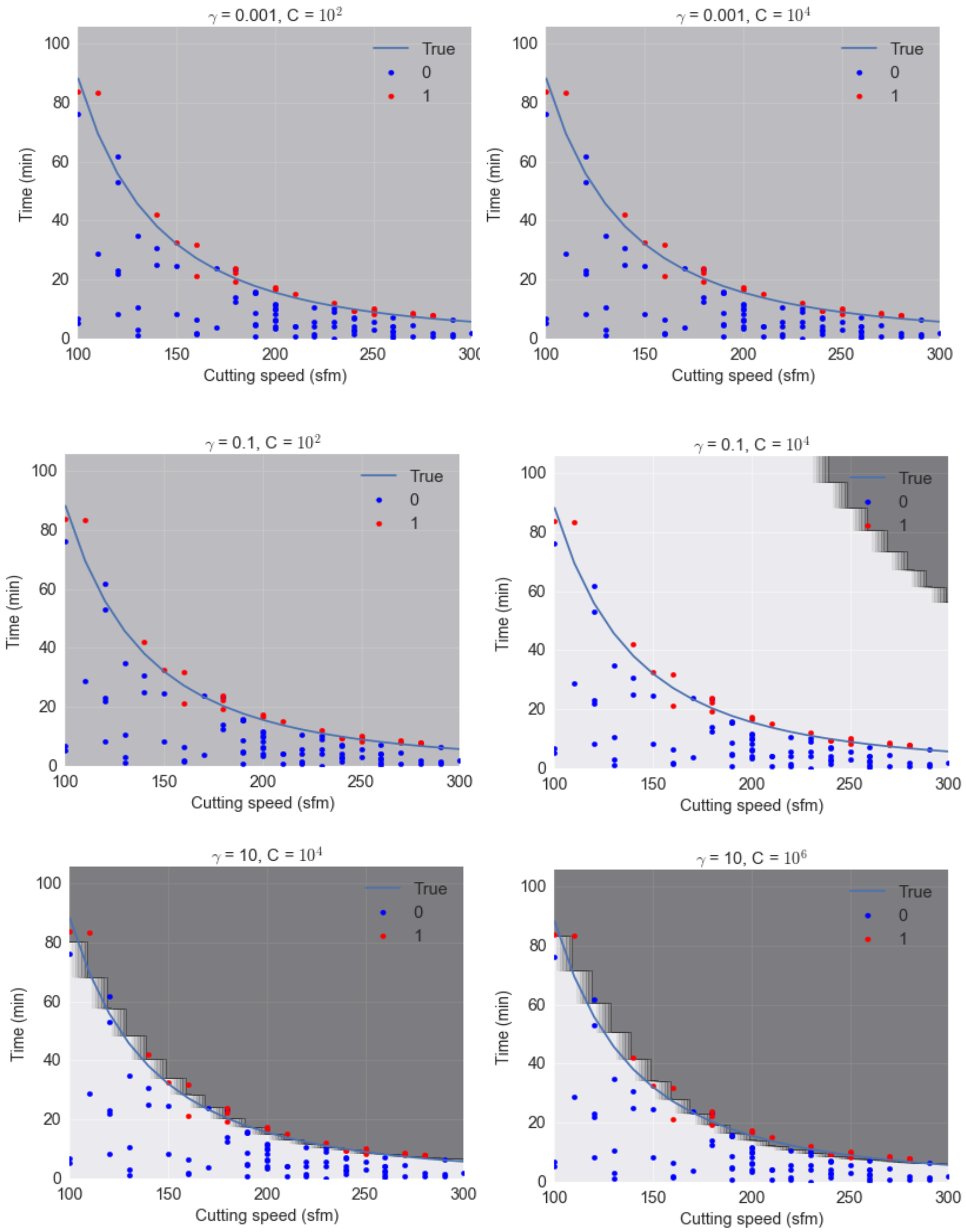


SVM Poly parameters:

γ = 10

C = 10

	n = 25	n = 50	n = 100	n = 500
RBF Poly	0.828	0.850	0.863	0.878



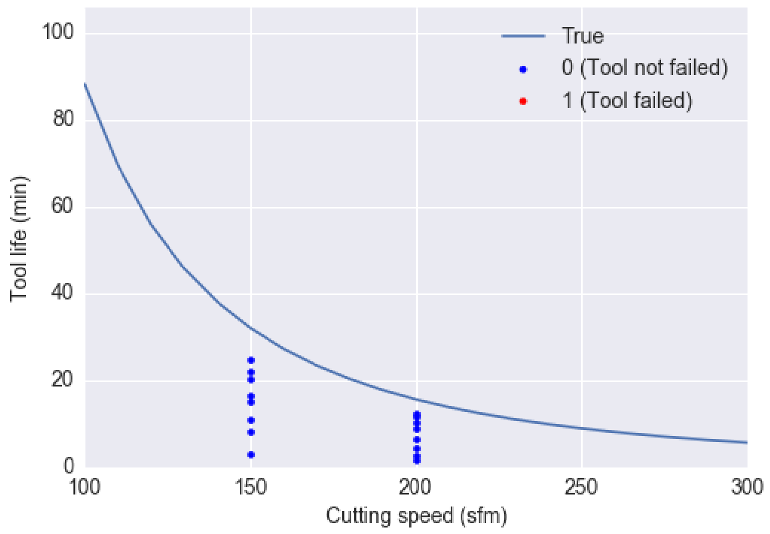
Influence of (C, γ) on SVM Poly classification

Sparse and imbalanced data

- Real life production data –
    - small # of data points
    - clustered at few spindle speeds
    - few or no failure points (class 1)

- Prediction not possible using machine learning classification

- Need to generate synthetic data based on knowledge of tool wear and user experience



Sparse and imbalanced data

- Add failure data points for every non-failure data point by extrapolating cut time to threshold wear value and applying a factor of safety

Example:

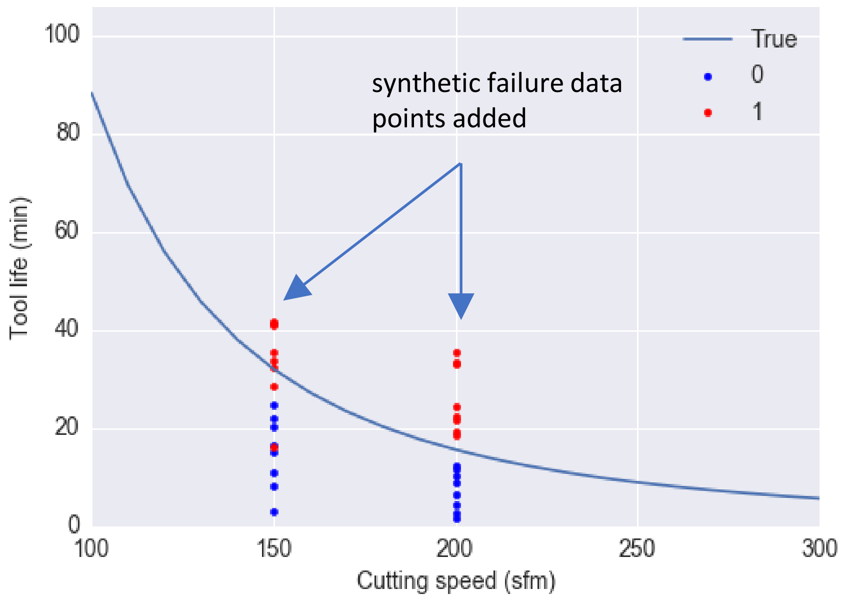
150 sfm, 16 minutes, wear 100 µm – Class 0

Threshold wear for tool failure - 300 µm

Linear extrapolation – 48 minutes

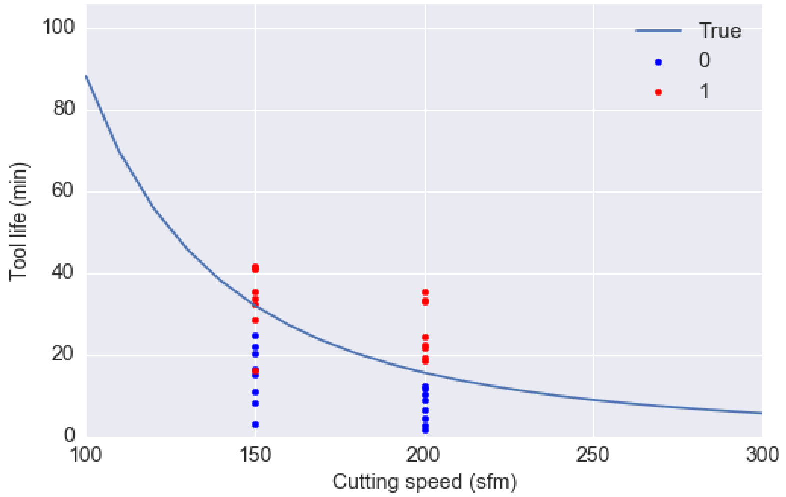
Factor of safety – 2

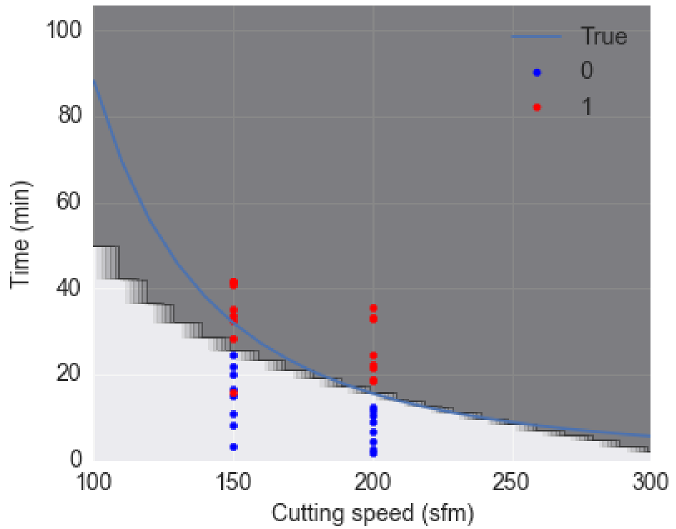
150 sfm, 96 minutes, wear > 300 µm – Class 1



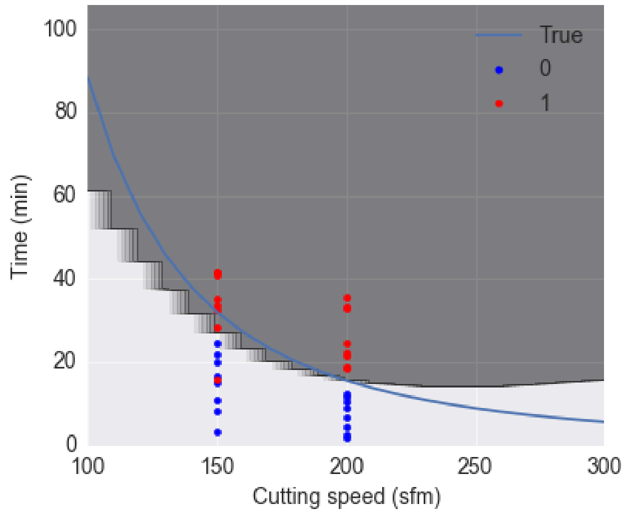
Sparse and imbalanced data

- Improved prediction by adding synthetic data points in the data range
- Model diverges from ‘true’ curve outside the data range

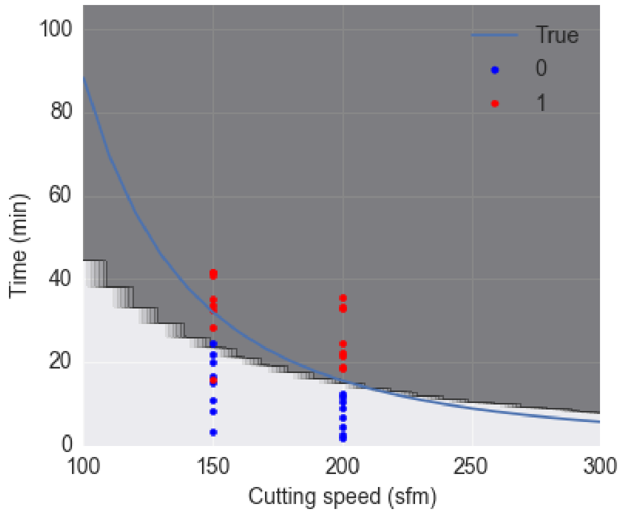




SVM RBF



SVM Poly



Logistic

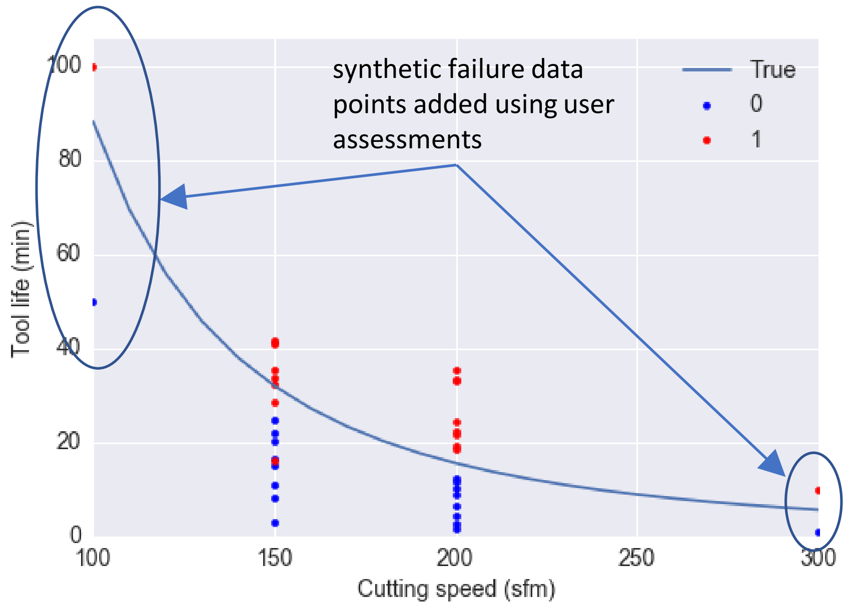
Sparse and imbalanced data

- Add data at spindle speed extremes using user assessments for tool life

Example:

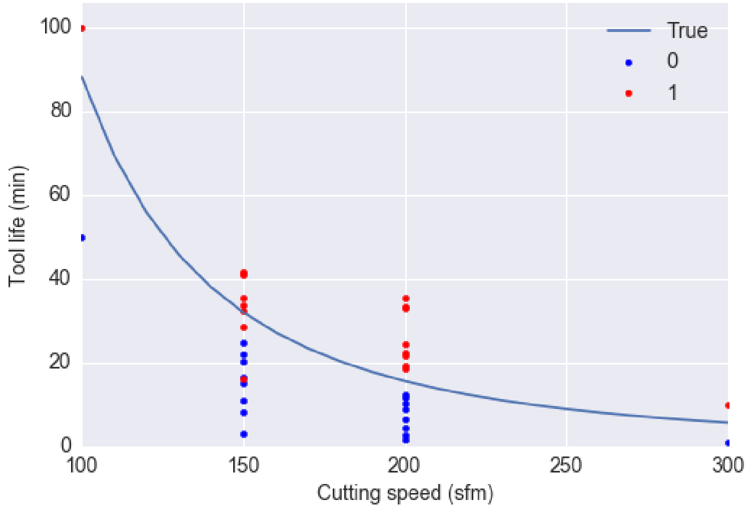
100 sfm, 50 minutes, wear < 300 µm – Class 0
100 sfm, 100 minutes, wear > 300 µm – Class 1

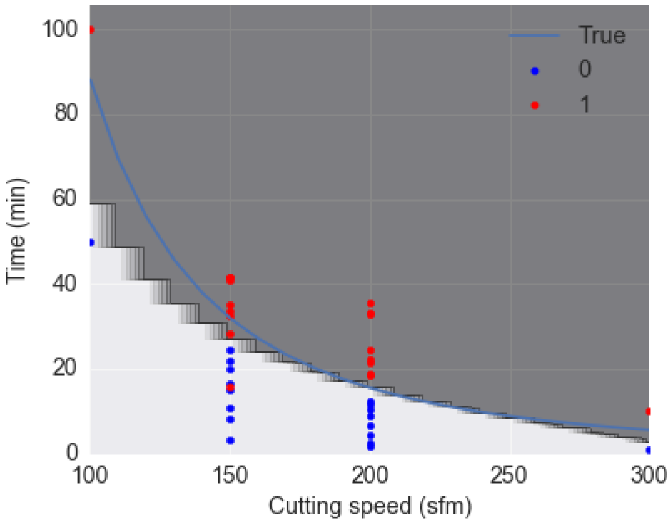
300 sfm, 1 minutes, wear < 300 µm – Class 0
300 sfm, 10 minutes, wear > 300 µm – Class 1



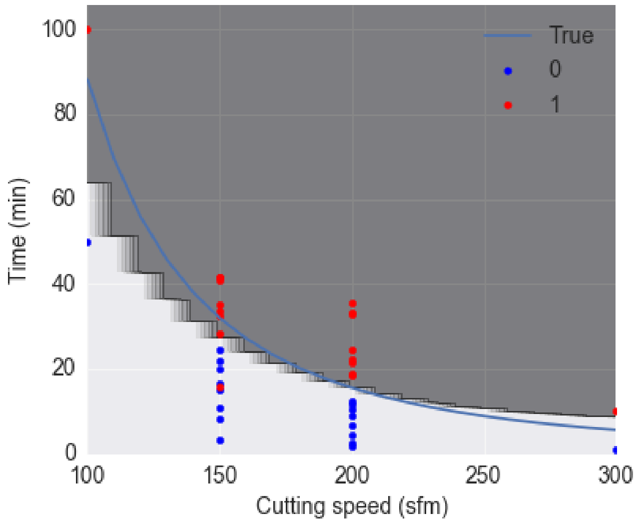
Sparse and imbalanced data

- Improved prediction by adding user assessment at the spindle speed minimum and maximum values

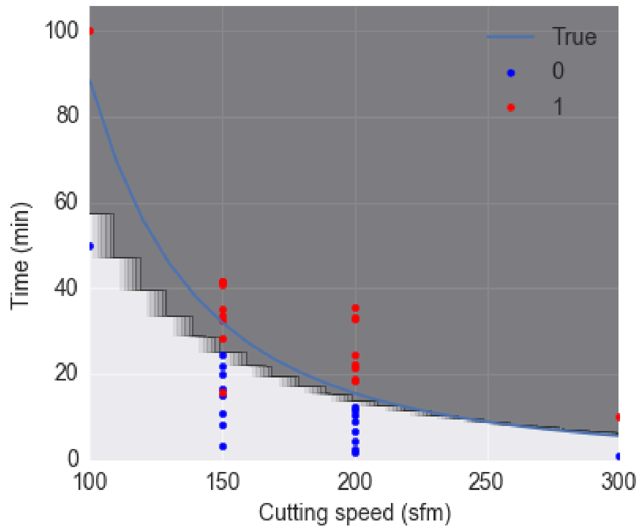




SVM RBF



SVM Poly



Logistic

Conclusion

- Machine learning classification – effective method of modelling tool life using production shop-floor tool wear data

- Data classified as:

    - class 0 : tool not failed (wear less than the threshold value)
    - class 1: tool failed (wear greater than the threshold value)

- Tool life modeled as classification boundary between class 0 and class 1 using machine learning methods
    - Support Vector Machines
    - Logistic