

Machine Learning and Failure Prediction in Hard Disk Drives

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What is Machine Learning

- Algorithms that:
 - Improve their performance P
 - At some task T
 - With Experience E
- Task: predict an event in the future
 - Will this hard drive fail?
- Training data: provides Experience
 - Reliability Test
- Performance: how many mistakes does it make?



In principle, similar to how a child learns from experience

A simple task, can you identify the object?

- Task T: Can you identify this object?



- Experience E:
 - Training Examples



- ➡ Apple
- ➡ Pear
- ➡ Tomato
- ➡ Cow
- ➡ Dog
- ➡ Horse

- Performance:
 - How many does it get right?
 - Other measures possible



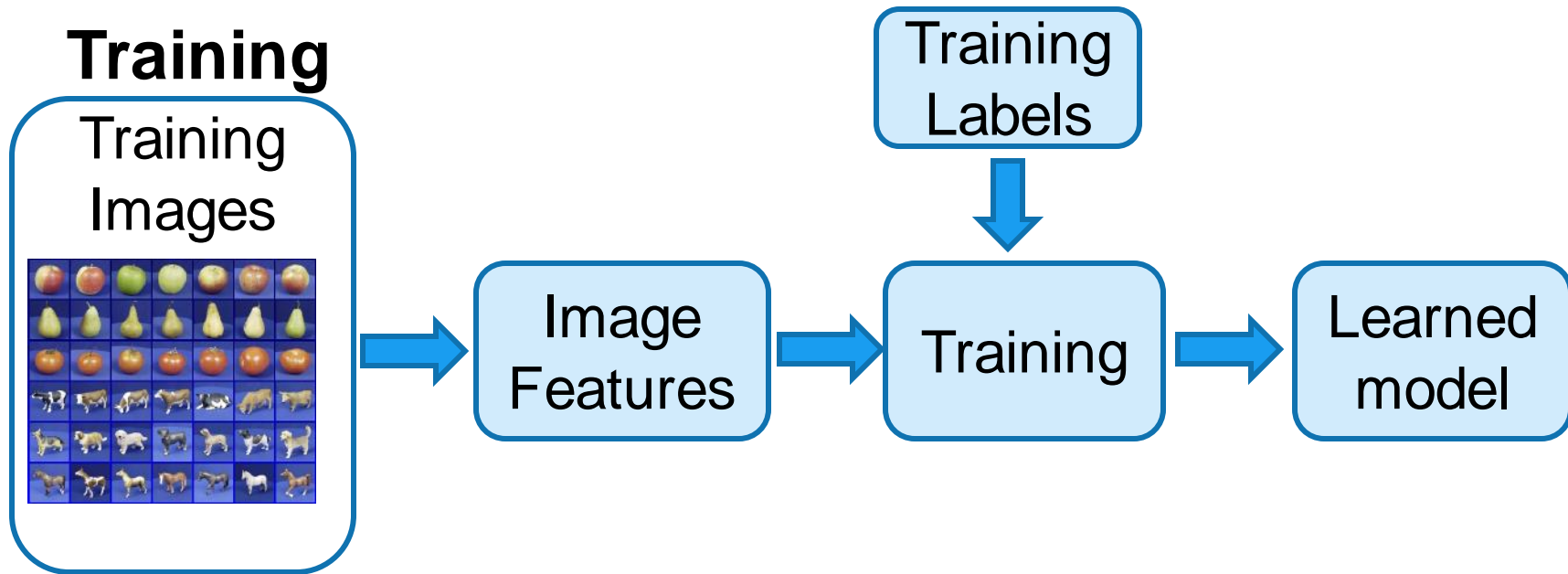
- *Often not simple manually coded Attributes*

- Compare to explicit Parameter based algorithm:

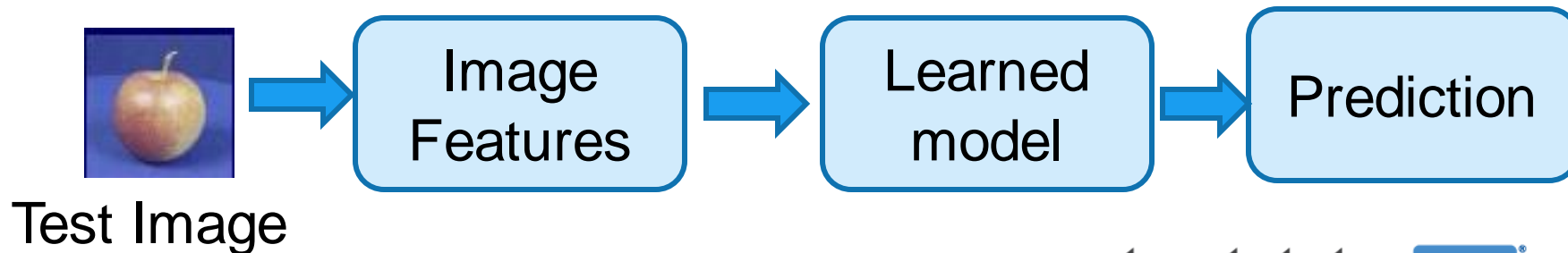
```
If (shape == round)
    then apple
else
    {
        if (four legged)
    }
```

Typical Workflow

Training



Testing

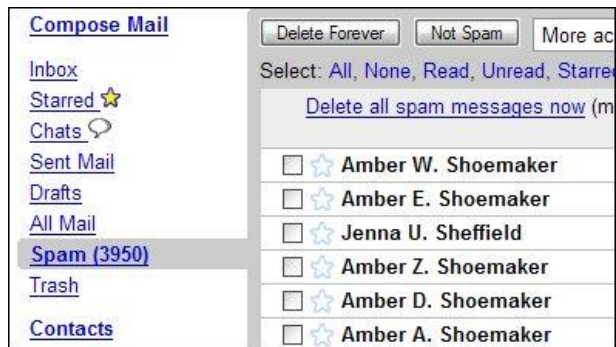


Where is machine learning used?

- Recommendation Engines



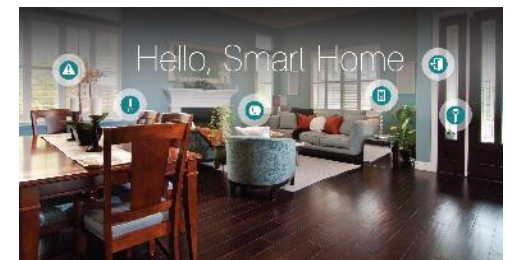
- A Spam filter



- Self driving Cars

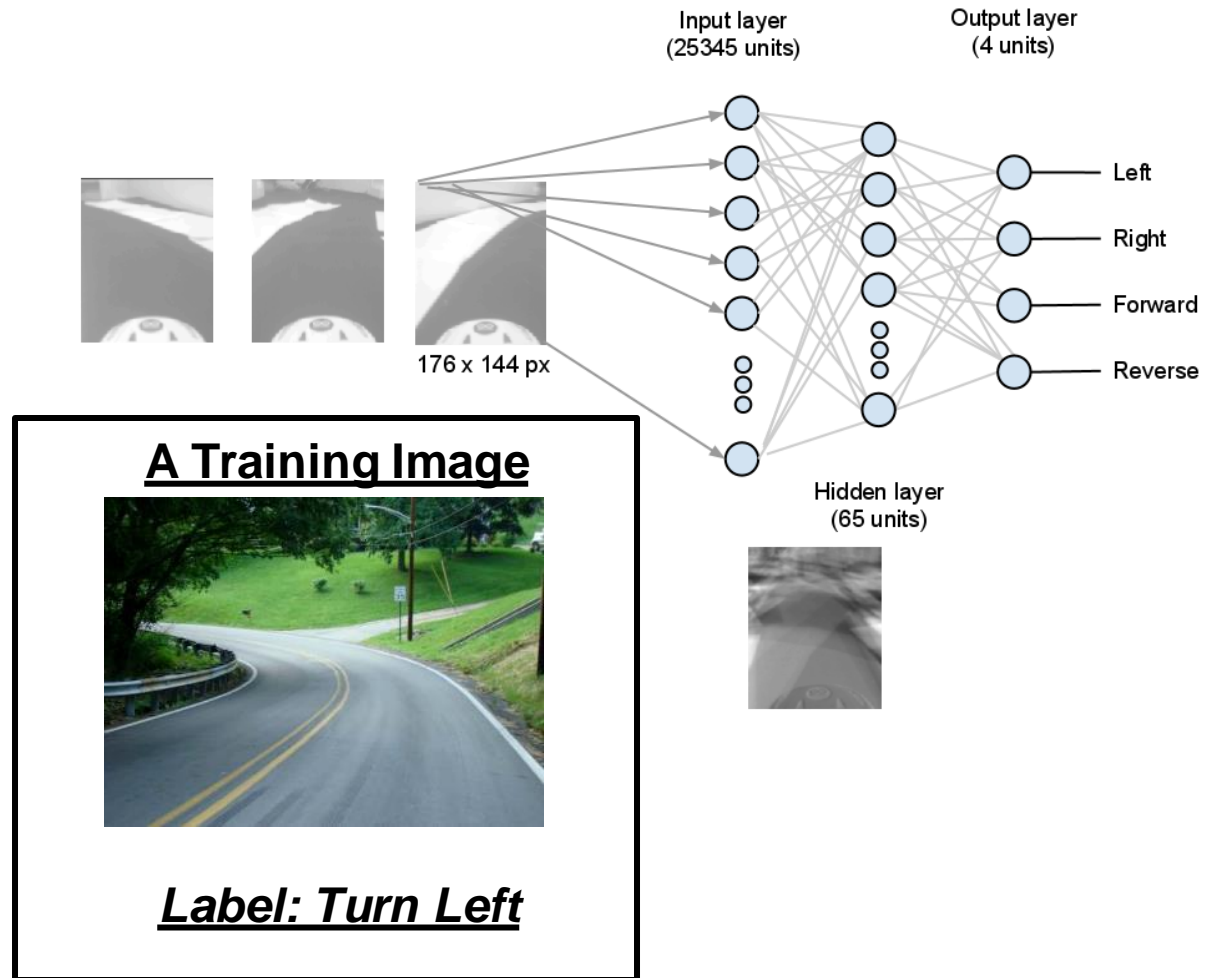


- Smart machines such as NEST thermostat

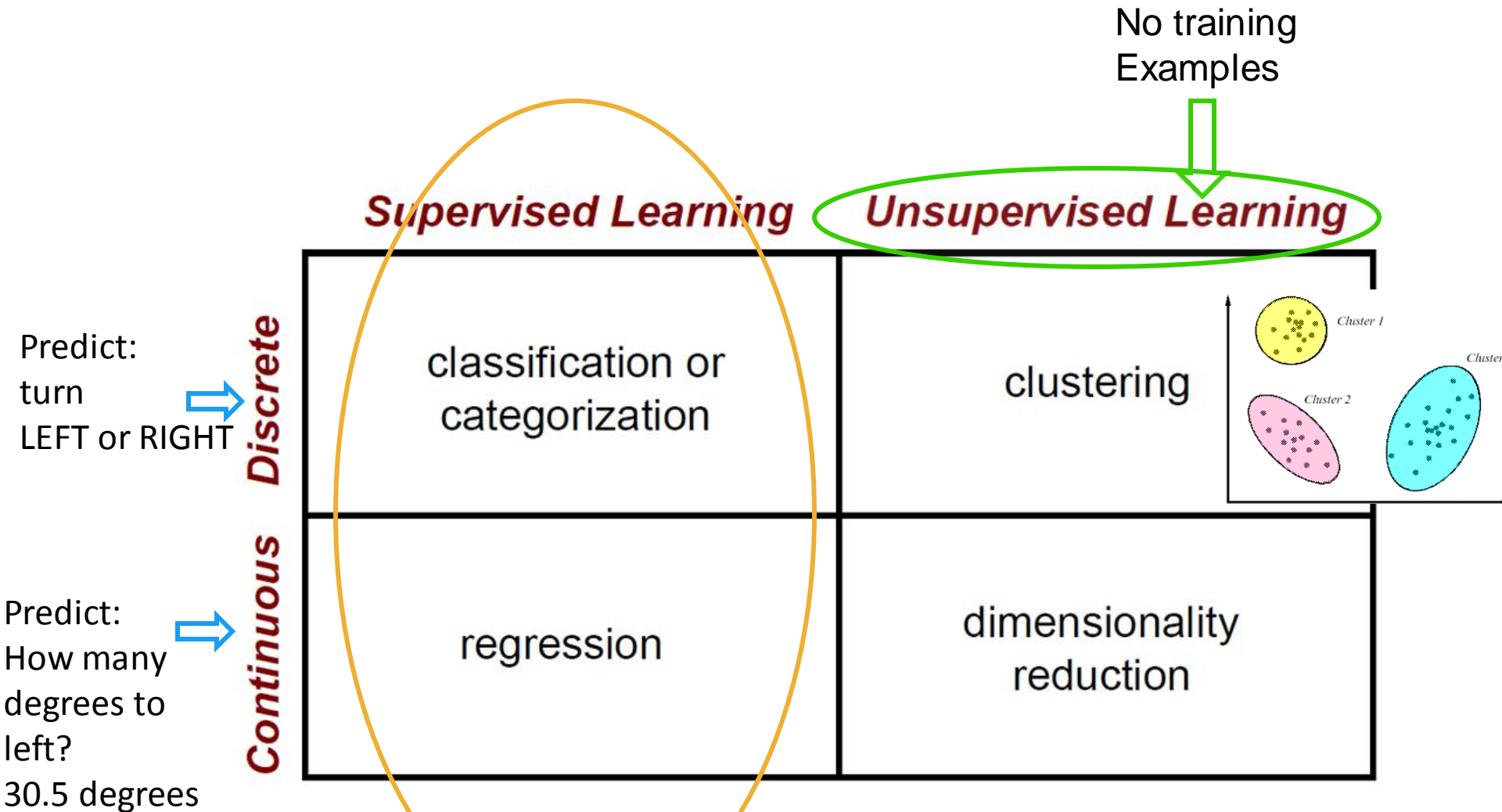


A more sophisticated example: Self driving car

- Can learn much harder tasks
- Not limited by simple parametric attribute based decisions
- Training
 - Images from windshield camera
 - Labels: driver action
- Feature: each pixel
- Lesson: Sophisticated algorithms can often solve problems better than human beings



Kinds of Machine Learning problems



Kinds of Machine Learning problems

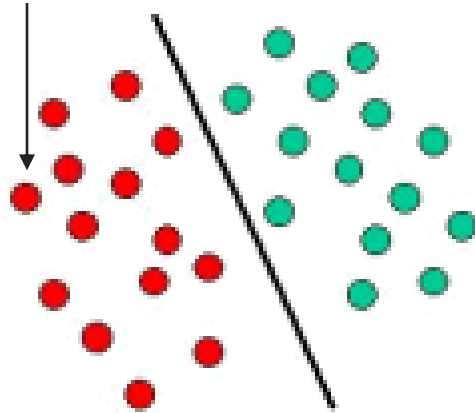
	<i>Supervised Learning</i>	<i>Unsupervised Learning</i>
<i>Discrete</i>	classification or categorization	clustering
<i>Continuous</i>	regression	dimensionality reduction

Classification Problems

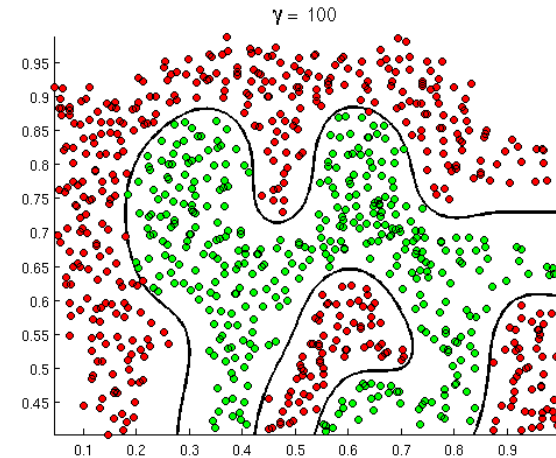
[<30,3>, Red]

Training
Examples:

- Points in 2D space
- <x,y>
- Label: Red/Green



Linear decision boundary



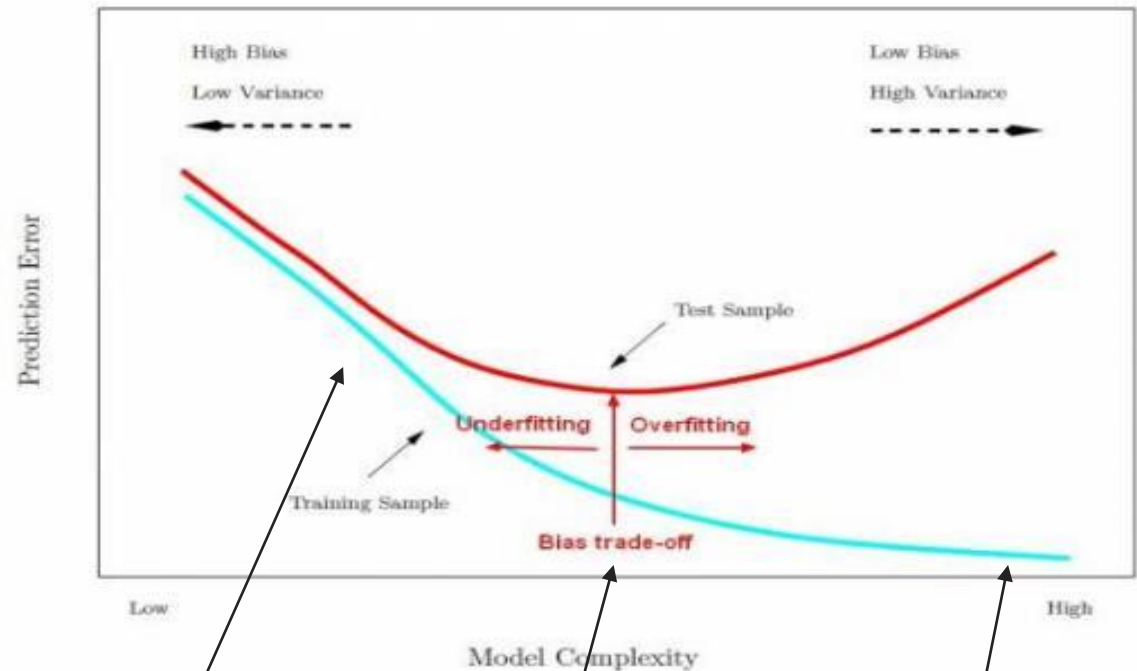
nonlinear decision boundary

- Functional approximation
- Define a function such that it divides positive and negatives
 - Linear: Easier and more robust (eg. Naïve Bayes, Logistic Regression)
 - Non Linear: Harder (eg. Support Vector Machine, Neural Network)

Issues in categorization

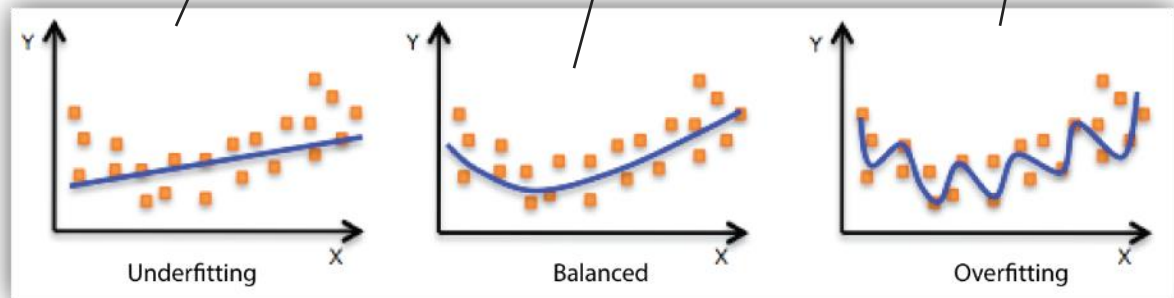
■ Can we generalize?

- May show very good accuracy with training data
- However not so much with test data



■ Think polynomial regression example

- Model complexity: Order of polynomial

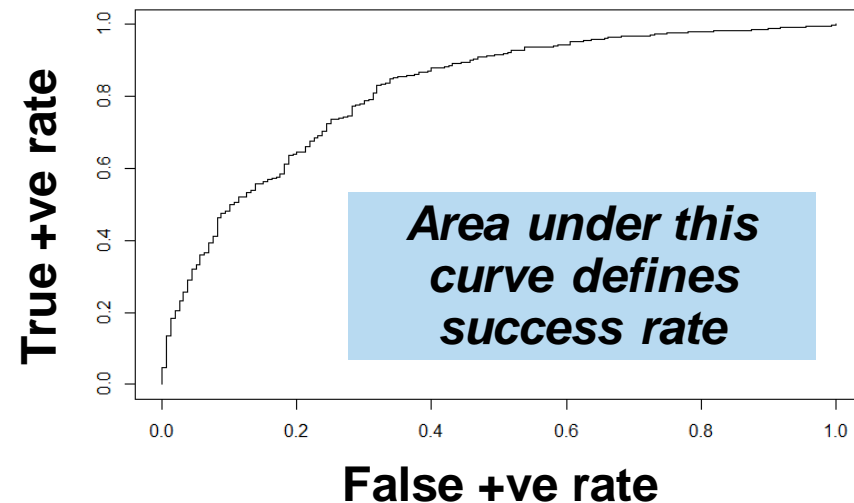


Confusion matrix and ROC curves

	p' (Predicted)	n' (Predicted)
p (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

■ Confusion Matrix

- 98 positives 2 negatives
- 98% accuracy not meaningful
- Does it predict true negatives?



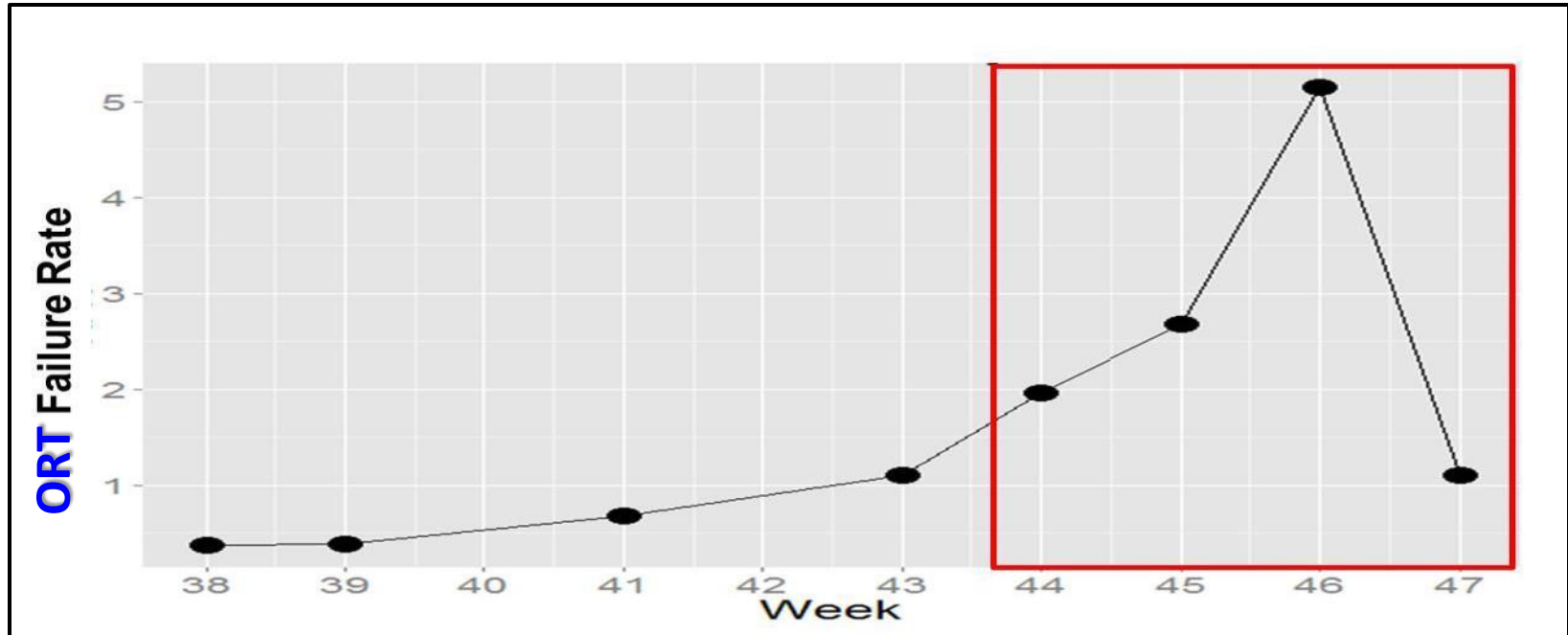
■ ROC curves

- Tradeoff between false positive and true positives
- How many false positives are we willing to accept?

How is Machine Learning relevant to Hard Disk drives?

Disclaimer: This presentation is mostly about “what is possible”

Let us demonstrate with 1 specific example on product A



- Every week we produce a large number of drives of this product (several 10s of 1000s)
- Sample some (200-300) drives from a 50,000 lot and run a stress test (**ORT** : **O**ngoing **R**eliability **T**est)

Problem statement –

- ORT shows an 'excursion' for 3 weeks of production
- The entire production lot during this time gets 'stop ship'ped
- Sitting on a large inventory of several \$M that needs action

What can we do?

Traditional solution – based on tribal knowledge/engineering insight

- Define “good” and “bad” explicitly, based on specific limit checks (If $A < \dots$ and $B > \dots$, then good)
- Run reliability tests on 300 “good” drives → to convince ourselves these are good
- Lose 6 weeks - that is the duration of the reliability test
- Trust that the rest of “good” drives will behave this way
- Ship and make \$

Machine Learning solution–

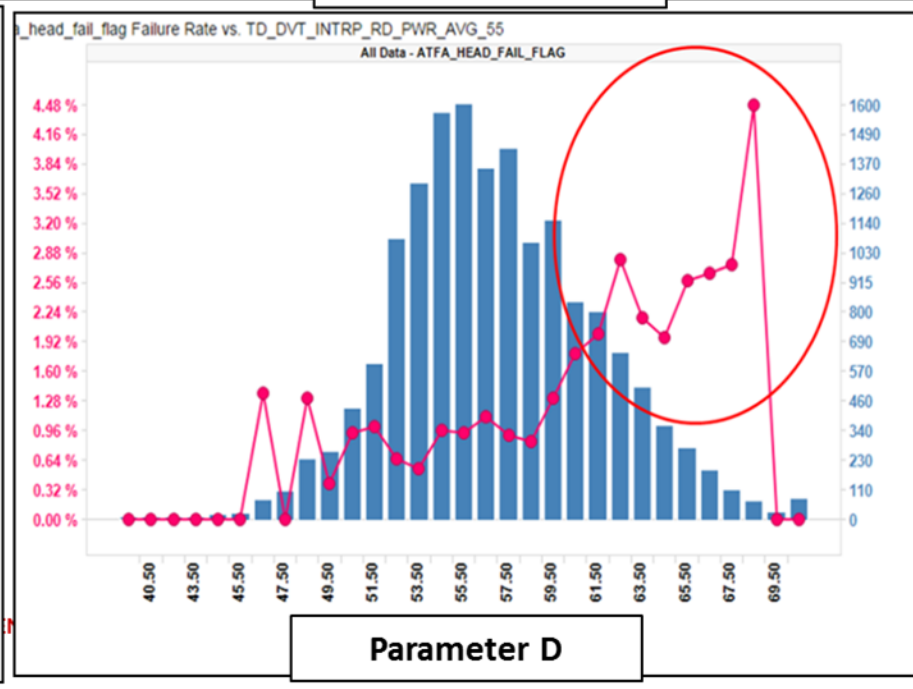
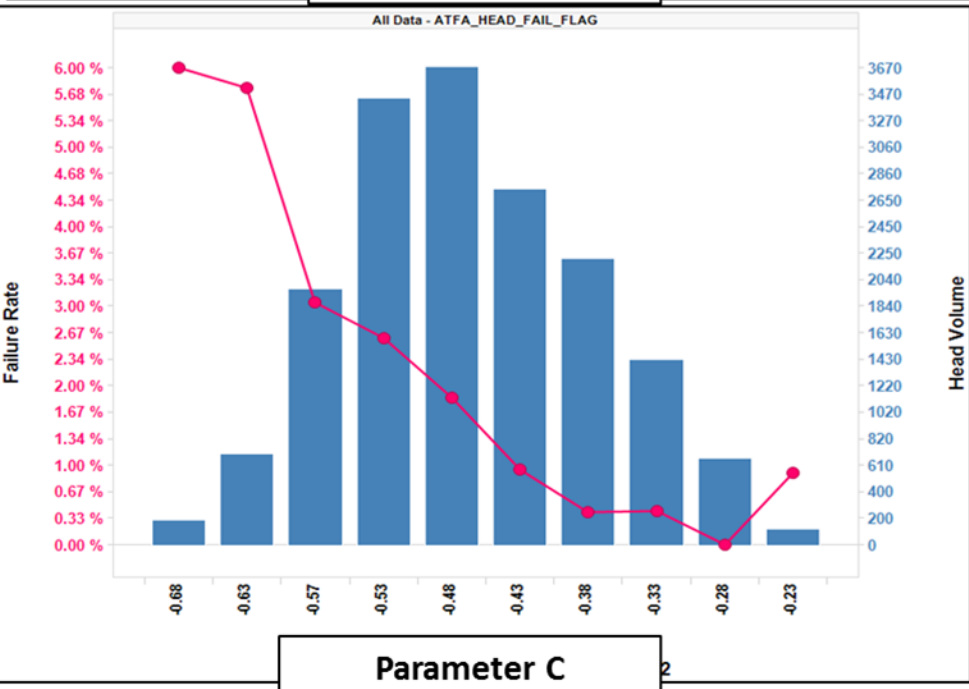
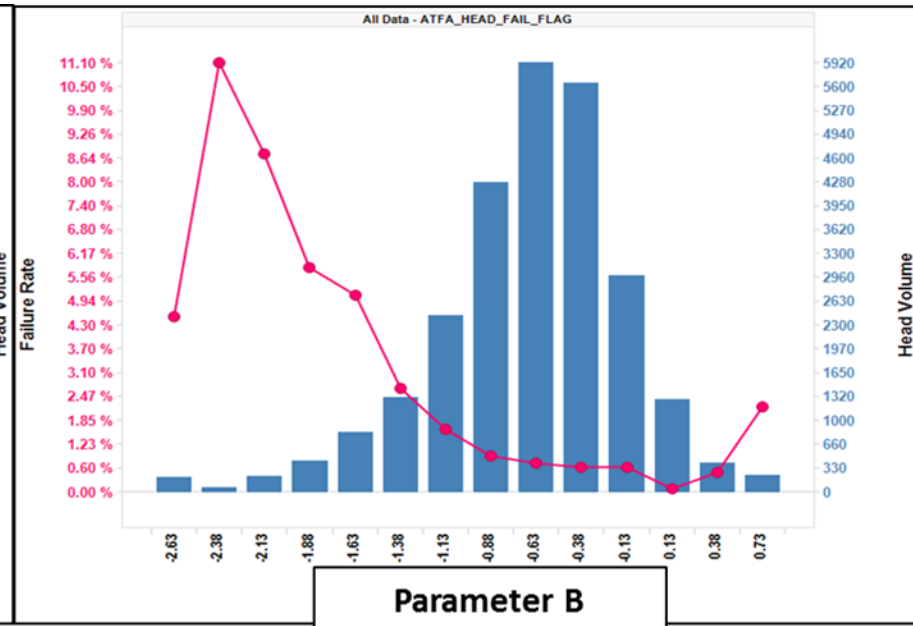
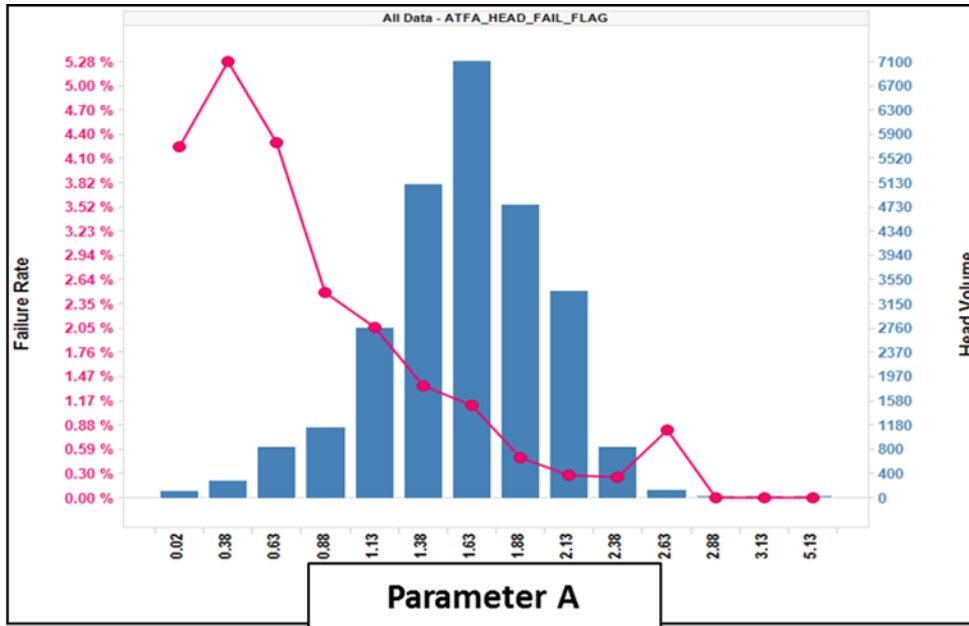
- Use Supervised Machine Learning on ORT data
- Supervisor: ORT failure rate –
 - Pass test : “good” drive
 - Fail test: “bad” drive
- Allow the algorithm to decide and build a predictive model of failure rate

Key benefit: Predict the failure rate without having to run the test !!

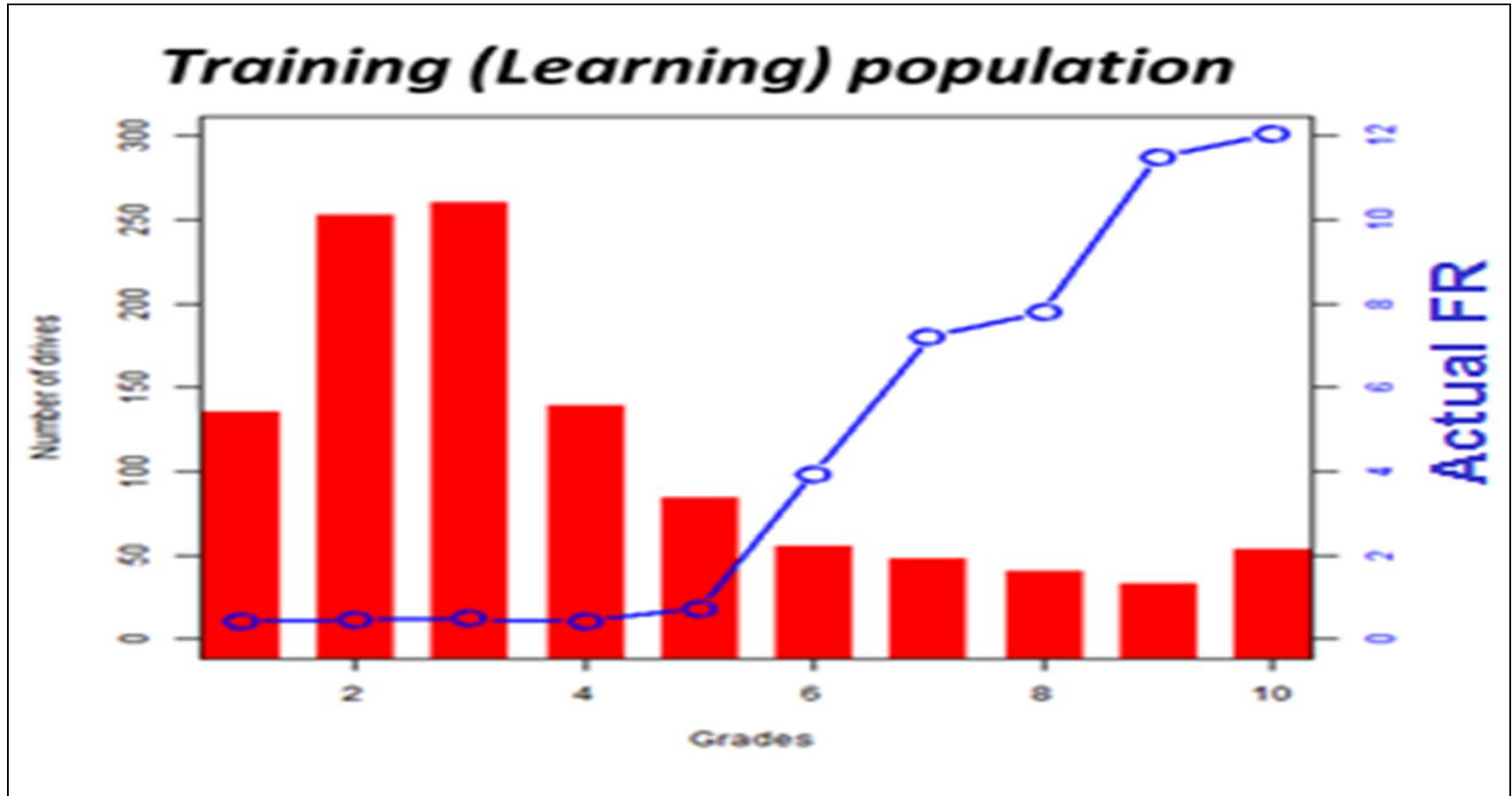
How is this done?

- ❑ Do a 50-50 split on the ORT population, into “Training” and “Test”
- ❑ Each drive goes through detailed characterization (about 2000 variables) before getting to ORT.
- ❖ On the “Training” population:
 - ❑ Use a classifier (χ^2 , Boosted forest,...) to choose the top 20-25 features from this variable list.
 - ❑ Build a Logistic Regression model. We can use others as needed (SVM, Neural Nets, Naïve Bayes etc)
 - ❑ Calculate the failure probability of each drive
 - ❑ Based on failure probabilities, generate a ‘health hierarchy’/grading system of drives before they get shipped
- ❖ Validate the model we just built on the “Test” set – it already has ORT data; how does the calculated failure probabilities match up

Failure Rate: sensitivity to key features chosen by the classifier



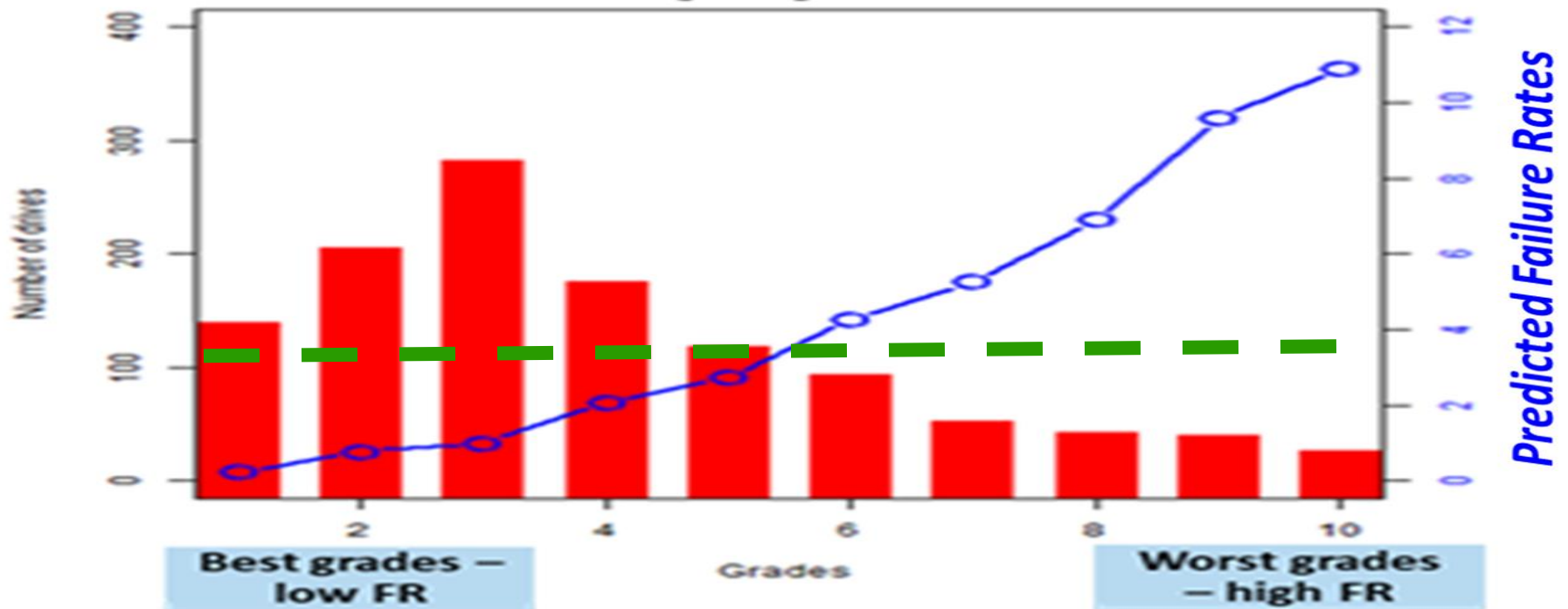
Model building on the 1st 50% (training set)



- ❑ These drives actually ran the test, so we can see how this holds up against real data
- ❑ If the learning was ideal , the blue line
 - would be the perfect classifier
 - Have all passers to the left, and all failures to the right

Model validation on the 2nd 50% ('test' set)

"Test" population



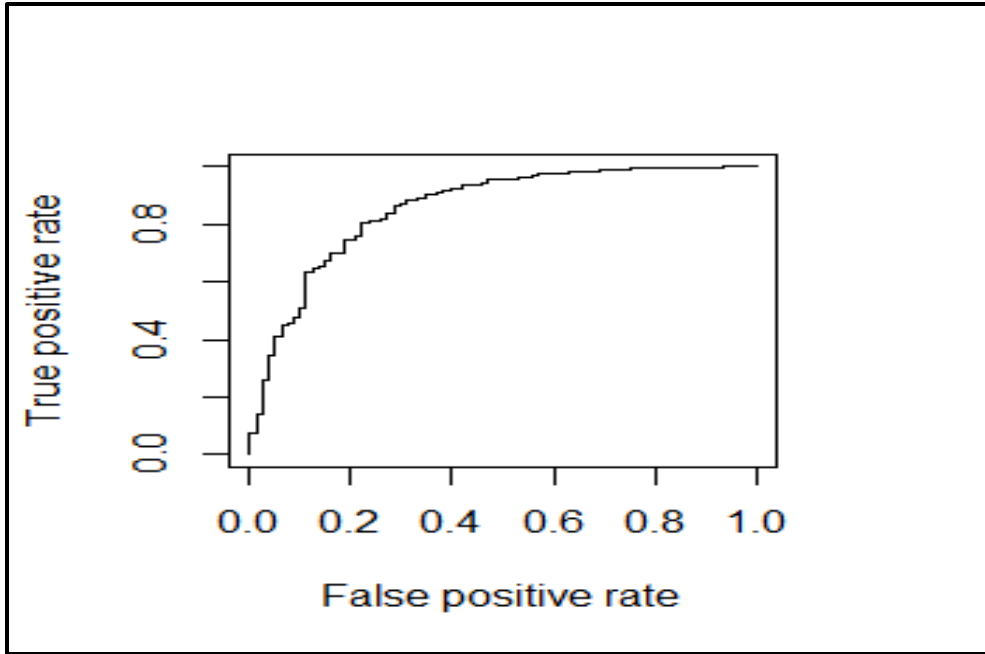
Then –

- Green dotted line: average actual Failure rate of this population
- This is all we had before - An average failure rate that looked bad

Now –

- Lot more insight. 10x spread in failure rates
- Grades 1-4 : pretty good drives;
Grades 8-10 : quite bad

Measures of success – ROC curve and TTF chart



- ❑ For this analysis, area under ROC curve ~ 85%-87%
- ❑ Algorithm making the right business call > 8 times out of 10.

Problem statement –

- ORT shows an 'excursion' for 3 weeks of production
- The entire production lot during this time gets 'stop ship'ped
- Sitting on a large inventory of several \$M that needs action

- ❑ Now we can use this algorithm on the entire production and calculate Failure Rate of each drive
- ❑ Appropriate business actions taken accordingly

Summary

- ❑ Drive Failure Prediction using Initial (Factory) conditions has always been tricky.
- ❑ Conventional methods do not have a high success rate – mostly under-predict
- ❑ Machine Learning allows us to approach the problem in a different way
- ❑ Still early, with continuous progress being made.
- ❑ This analytical technique, coupled with periodic in-field measurements, can provide a robust framework for fleet management.

Thank you !