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Uncovering Opportunities: How Finance Executives Can Use Machine Learning To Gain A Leading Edge

Webinar

Tuesday 20 October 2020





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Agenda

- | | |
|---------------|--------------------------------------|
| 16:00 – 16:05 | Chairman's Introduction |
| 16:05 – 16:30 | Keynote Address – Chandu Chilakapati |
| 16:30 – 16:45 | Questions & Answers |



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Uncovering Opportunities: How Finance Executives Can Use Machine Learning To Gain A Leading Edge



Chandu Chilakapati

Managing Director

Alvarez & Marsal
Valuation Services

Uncovering Opportunities: How Finance Executives Can Use Machine Learning To Gain A Leading Edge

October 2020

ALVAREZ & MARSAL
LEADERSHIP. ACTION. RESULTS.™

Webinar: Chandu Chilakapati



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Session Objectives

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Machine Learning for Finance Executives

- *What is Machine Learning?*
- *How do I use it?*
 - *What problems would be a good fit for Machine Learning?*
 - *Prepare data*
 - *Understand the algorithms*
 - *Understanding accuracy and improving the outputs*
- *Case Study: LeaseSCRE*

What is Machine Learning?

What is Machine Learning?

My Definition

“Machine Learning is a subset of Artificial Intelligence that is focused on training computers to use algorithms to make predictions or classifications using provided data.”

Sounds complicated, but once you have the algorithm it is no different than other statistics that you use regularly like average, median, frequency, probability, etc.

How ML Will Impact the Finance Function

Prediction for Next Five Years

Inputs

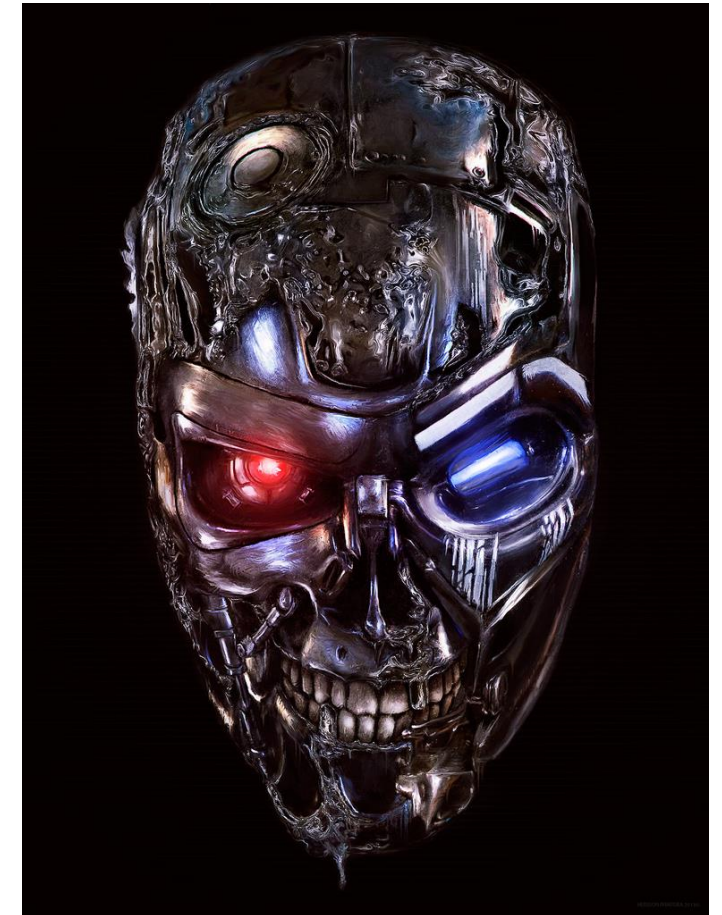
- Many key inputs will be informed by ML models
- Analysts will analyze **data** supporting those inputs

Outputs

- Industry knowledge will become highly valued
- Quicker turnaround
- Accurate delivery

People

- Machines will not replace humans
- Analysts will have to identify when the ML model misses
- UNDERSTANDING THE PROBLEM AND SOLUTION ARE KEY...



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What Kind of Problems Can Machine Learning Solve?

Project Suitability for Machine Learning

The Three Key Questions

Does the Project Match the Characteristics of a Typical ML Problem?

- Supervised vs Unsupervised
- Simple model... $A+B = C$ versus
- Complex model... $A+B+\dots+F(X) = Z$

Is there a Solid Foundation of Data?

- The need for observable outcomes...credit rating example
- Text needs to be transferred to numerical data with observable outcomes
- Use your own organization's data
- More is not always better

Understanding the Payoff – The Human Factor

- To get best results, analysts and expertise are required to understand the results

SCRE – Sample Credit Rating Estimator

Credit ratings are important for valuation of debt, equity, and businesses in general

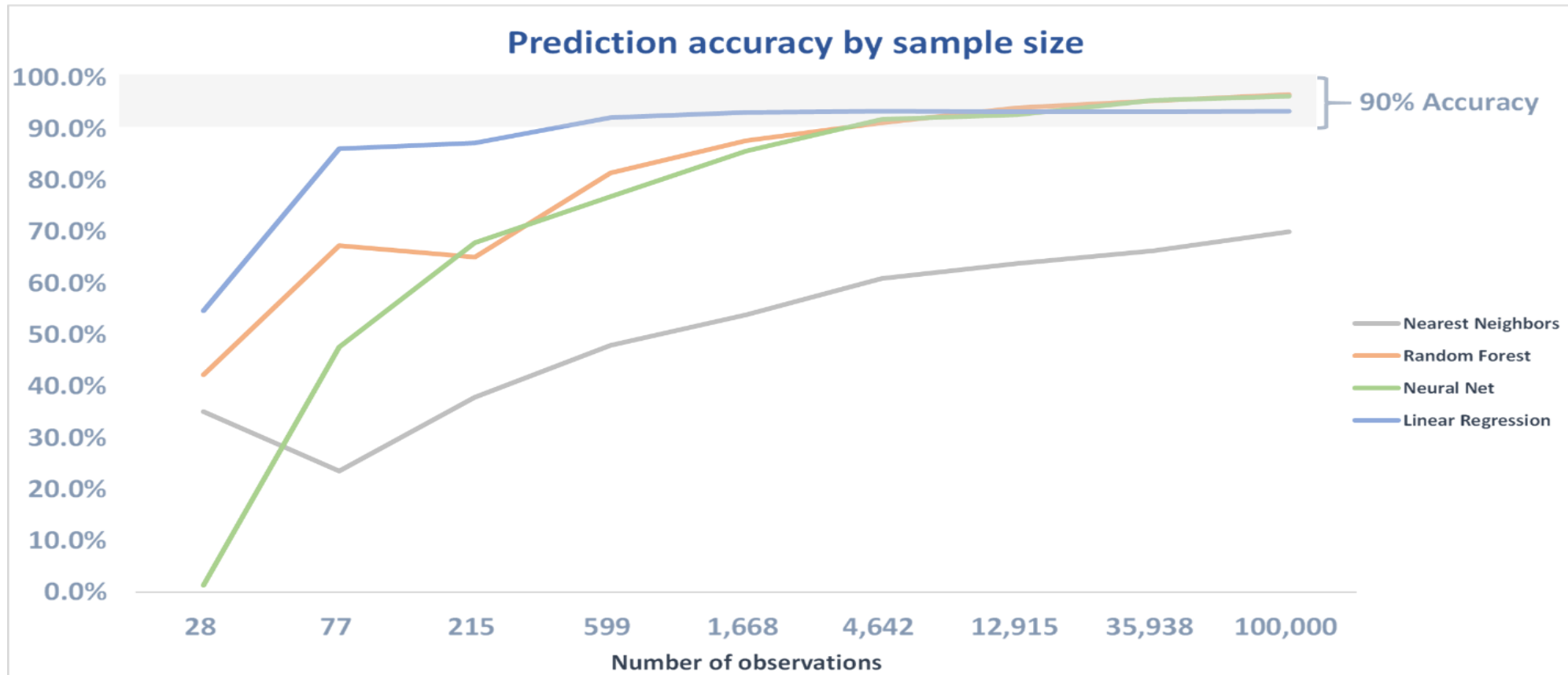
- Debt valuation was the start of our ML journey
- The methods currently employed seemed extremely biased
- Regression was considered the best approach but didn't test well
- Ratings agencies have a monopoly on credit and are notoriously late to downgrade
- Public company data was readily available
- We are experts in the field

Selecting and Preparing Data for Machine Learning

Selecting and Preparing Data

The models are trained and tested on data

How Much Data is Needed?



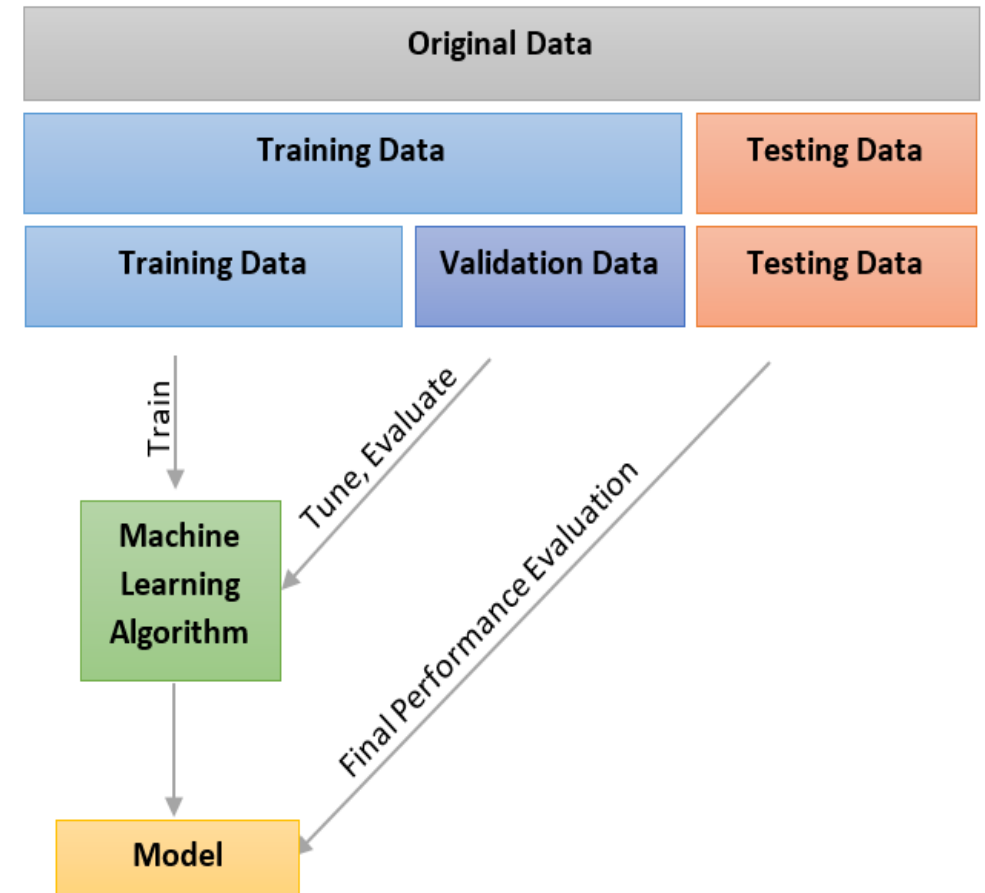
Selecting and Preparing Data

Data must be segregated into a train and test set for the model to learn from it appropriately and test it

Pitfalls to avoid

- Cross Contamination between train and test data
- Converting text or numeric data to be meaningful
- Consider whether there is implicit or explicit bias in the data

From <http://magizbox.com/training/machinelearning/site/evaluation/>



Understanding and Assessing Machine Learning Algorithms

ML Algorithm Overview

- **K-Nearest Neighbors**
- **Regression**
- **Support Vector Machine**
- **Decision Trees**
- **Neural Networks**

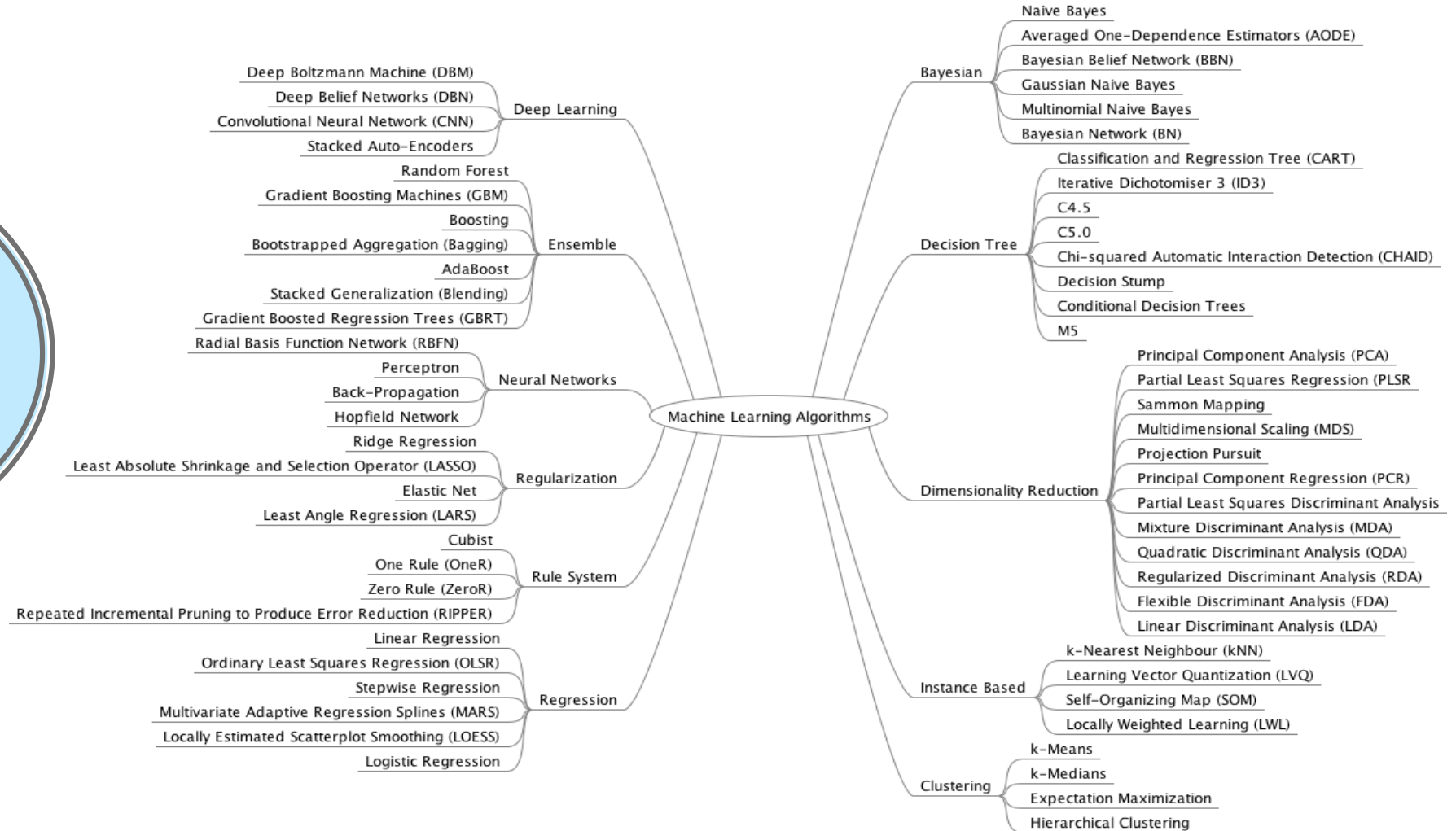
		Regression Analysis	k-Nearest Neighbors	Support Vector Machine	Decision Tree	Random Forests	Neural Networks
Prediction	Binary Outcomes	✓	✓	✓	✓	✓	✓
	Categorical Outcomes		✓		✓	✓	✓
	Class Probabilities	✓	✓		✓	✓	✓
	Continuous Outcomes	✓	✓		✓	✓	✓
	Non-linear Relationships		✓	✓	✓	✓	✓
Analysis	Large Number of Variables			✓	✓	✓	✓
	Simple to Use	✓	✓		✓	✓	
	Fast Computation	✓			✓		
Results	Highly Accurate					✓	✓
	Interpretable	✓	✓		✓		

Chart from [Numsense! Data Science for the Layman: No Math Added](#)

Assessing an Algorithm

Algorithm Overload

Overview of Machine Learning Algorithms



Assessing the Algorithm

You don't have to be a data scientist to assess whether an algorithm is a good solution for the problem

1. Is this a Classification or Prediction Problem?
2. Does the outcome require a discrete number classification or prediction?
3. Are you looking for outliers?

Machine Learning Accuracy and Outputs

Do You See ML as a Black Box?

How do we know its right?



ML Accuracy: Assessing Accuracy and Improving Outputs

Experts not just data scientists needed

What do test and train results mean?

- Train and Test results that are aligned are best
- Underperformance of testing vs. training is a good sign that your data doesn't support the algorithm and the model is overfitting
- High test scores are best... DUH!
- Processing time might be relevant

Actual SCRE results

```
Nearest Neighbors train 84.80% test 77.64% (0.925s)
SGD train 62.76% test 60.13% (0.181s)
Decision Tree train 100.00% test 77.87% (1.095s)
Random Forest train 99.77% test 83.72% (0.493s)
Neural Net train 59.34% test 58.60% (2.950s)
AdaBoost train 71.37% test 70.49% (5.900s)
Naive Bayes train 22.89% test 22.95% (0.160s)
QDA train 37.39% test 37.60% (0.216s)
Linear SVC train 70.67% test 66.24% (40.671s)
Logistic Regression train 49.31% test 49.43% (28.974s)
Linear SVM train 59.03% test 43.62% (51.722s)
RBF SVM train 50.31% test 54.82% (86.386s)
```

ML Accuracy: Assessing Accuracy and Improving Outputs

Experts not just data scientists needed

- Select model
- Test the data and results
- Adjust and retrain and test
- Repeat until the dataset is best for training
- Those results are with every feature and an example of overfitting

Actual SCORE results

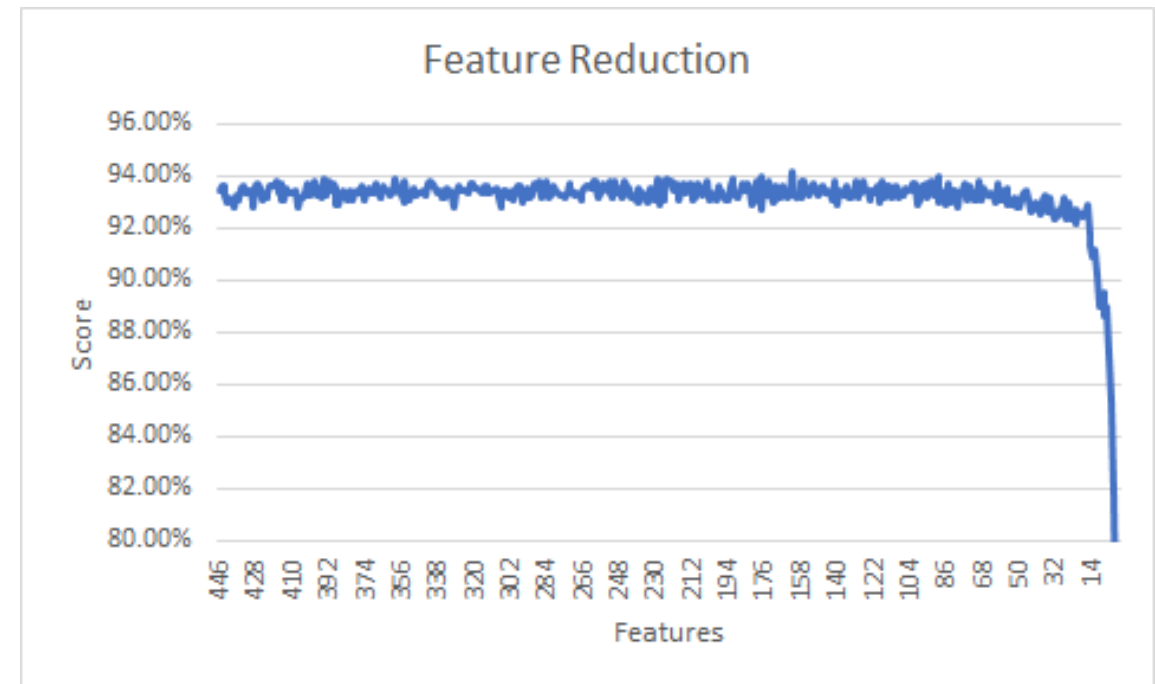
```
Nearest Neighbors Regressor train 72.09% test 63.17% (1.153s)
SGD Regressor train 0.00% test 0.00% (0.251s)
Decision Tree Regressor train 100.00% test 95.35% (3.955s)
Random Forest Regressor train 99.94% test 97.69% (3.773s)
Neural Net Regressor train 0.47% test 0.57% (5.625s)
AdaBoost Regressor train 80.88% test 81.50% (32.767s)
Linear SVR train 74.06% test 74.21% (13.829s)
Linear SVM Regressor train 70.38% test 71.01% (192.301s)
RBF SVM Regressor train 59.99% test 61.11% (219.249s)
Gaussian Process Regressor train 100.00% test 0.83% (238.731s)
Linear Regression train 70.74% test 70.62% (0.544s)
Ridge Regression train 70.55% test 70.72% (0.274s)
Lasso train 54.25% test 55.56% (10.432s)
Elastic Net train 54.32% test 54.94% (10.864s)
Lars train 0.00% test 0.00% (0.397s)
Lars Lasso train 44.42% test 44.42% (0.290s)
Orthogonal Matching Pursuit train 68.68% test 69.24% (0.290s)
Bayesian Ridge Regression train 70.48% test 70.66% (0.587s)
Perceptron train 52.56% test 52.47% (0.824s)
Passive Agressive Regressor train 8.19% test 8.14% (0.287s)
Random Sample Consensus Regressor train 48.30% test 47.91% (2.391s)
Theoretical Considerations train 72.55% test 72.49% (769.393s)
Huber Regression train 35.36% test 35.19% (1.919s)
```

ML Accuracy: Assessing Accuracy and Improving Outputs

Experts not just data scientists needed

- Use Principal Component Analysis to test relevance of features
- Reduce to the point where the model is agile while maintaining accuracy
- Tune the model to optimize with the new features selected

Actual SCRE results

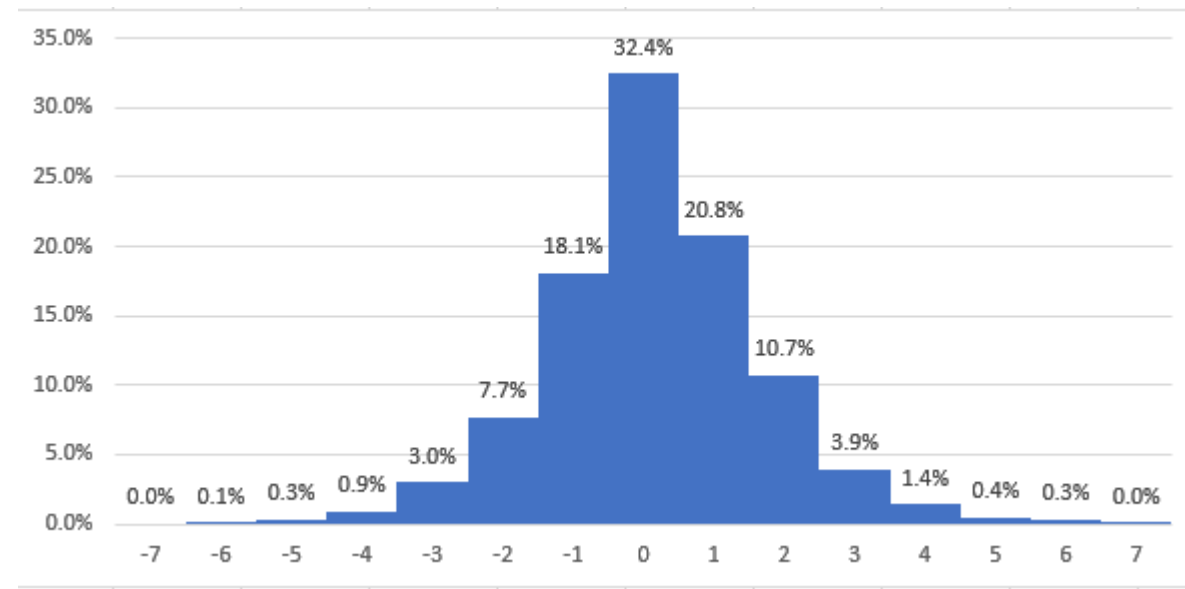


ML Accuracy: Assessing Accuracy and Improving Outputs

Experts not just data scientists needed

- Test and investigate results
- Visualization software may be helpful
- Be careful of high accuracy with large misses
- Consider using other ML algorithms to test

Results are not representative of final SCORE model



Case Study: ML and How to Estimate your Incremental Borrowing Rate

LeaseSCRE

Machine Learning Solving a Finance Problem

Problem:

- New accounting standards ASC842 and IFRS16 require companies to put the present value of operating lease payment obligations on-balance-sheet discounted at an Incremental Borrowing Rate (IBR)
- Need credit rating to determine IBR

Solution:

- Create a ML model to predict the credit rating using historical data of public companies (SCRE)
- Test the model and compare to alternatives
- Create the documentation and support for the model to be able to convince stakeholders of results
- Grab a pint because problem solved!

Resources

Machine Learning For Finance Executives

A compendium of articles to help financial executives insert themselves into the conversation about the right data to use, apply their institutional knowledge and understand the key principles of machine learning.

<https://www.alvarezandmarsal.com/content/opening-black-box-assessing-machine-learning-models>

LeaseSCRE: Online, ML-powered, tool for estimating IBR

<https://www.alvarezandmarsal.com/leasescre> - link to site and demonstration

Chandu Chilakapati

Valuation Services | Managing Director

Chandu Chilakapati is a Managing Director with Alvarez & Marsal Valuation Services in Houston. He specializes in fair value and financial reporting of financial instruments, as well as traditional business and asset valuation advisory services. He is the national Energy Valuation lead and Head of Innovation.

Mr. Chilakapati is one of the founders of **LeaseSCORE**, a machine-learning software that estimates a company's incremental borrowing rate (IBR). **LeaseSCORE** costs a fraction of third-party advisory services for estimating an IBR and with machine learning, it is also a more accurate tool for estimating credit ratings to derive the IBR.

Full Bio: <https://www.alvarezandmarsal.com/our-people/chandu-chilakapati>



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QUESTIONS & DISCUSSION, ANSWERS?





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- Wednesday 21 October (12:00) [Employee Share Schemes: Innovative Communication Strategies Guaranteed To Increase Employee Take-Up](#)
- Thursday 22 October (11:00) [Nature Smart Cities: Innovative Financial Mechanisms To Support Local Authorities With Urban Greening](#)

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