Machine Learning & Non-Parametric Methods for Cost Analysis

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Machine Learning Approach to Cost Analysis

Machine Learning in General

ML* Algorithms for Cost Analysis

ML Applications related to Cost

- Random Forest Prediction
- Latent Semantic Analysis

Challenges

* ML = Machine Learning
Machine Learning Buzz Words

- Big Data
- Smart Manufacturing
- Deep Learning
- NLP (Natural Language Processing)
- IOT (Internet of Things)
- Predictive Analytics
- Neural Networks
- Autoencoders
- Feature Extraction
What is Machine Learning?

Simply, when a machine mimics "cognitive" functions such as "learning" and "problem solving" *

Machine Learning (ML) is a method in which algorithms …

▪ teach themselves to grow (i.e. learn) from data
▪ learn without being explicitly programmed

Machine Learning is a type of Artificial Intelligence

What can Machine Learning do?

- Speech recognition
- Autonomous scheduling
- Financial forecasting
- Spam filtering
- Logistics planning
- VLSI layout
- Automatic assembly
- Information extraction
- Market Share Analysis
- Route finding

- Robotics
  - household, surgery, navigation
- Failure prediction
- Fraud detection
- Web search engines
- Autonomous cars
- Energy optimization
- Question answering systems
- Social network analysis
- Medical diagnosis, imaging
- Document summarization

Many applications for Machine Learning
Why is Machine Learning so popular now?

Machine Learning has been around for a long time

- Has become more popular recently

Data Explosion

- Much more data available for complex analyses

Machine Power

- Moore’s Law: faster and cheaper computers

Accuracy of Algorithms

- Reliable enough for usable products

The Future is Here
How does Machine Learning Work?

Typically consists of two stages

- Training phase

- Testing Phase

*General Process*
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Machine Learning for Cost Prediction & Analysis

Typical Cost Prediction Methods

- Analogies
- Engineering / Bottoms up
- Parametric Equations / Top down

Machine Learning

- Alternative to traditional cost estimating
- Age of Big Data & Messy Data
- Interactions and non-linear behavior
- Relationship not well understood nor apparent
- Relatively quick & easy to implement

Could we use Machine Learning techniques for cost prediction?
Supervised Algorithms

K-Nearest-Neighbors (KNN)
- Clustering approach
- Given new features, finds nearest example and return its value

Key features
- Regression and Classification

Support Vector Machines (SVM)
- Clustering approach
- Finds the widest margin between classes (boundary decisions)

Key features
- Able to separate non-linearly-separable regions

Fast Classification, Similarity Detection

Able to find Optimal Solutions
Supervised Algorithms

Neural Networks (NN)
- Multi-layer perceptron model
- Finds weights for inputs that optimize the cost function

Key features
- Very complex shapes/decision boundaries
- Needs a lot of data

Random Forest Prediction
- Decision Tree Ensemble
- Each tree is built from a sample (random) set of features

Key features
- Training set can be small
- Regression & Classification

Finds patterns in large amounts of data

Handles small n, large p problems
Unsupervised Algorithms

Natural Language Processing -
Latent Semantic Analysis (LSA) / Latent Dirichlet Allocation (LDA)

▪ Document Clustering
▪ Information retrieval in document groups

Key features
▪ Automatic topic detection
▪ Key term discovery
▪ Word Clustering

Automatic Document Grouping
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Trees and Forests

A Single Decision Tree
- Represents a set of decisions
- Easily interpretable, but …
- Not a great predictor

An Ensemble of trees
- Many trees (100s)
- Not as easy to interpret, but …
- Provides greater prediction accuracy & more stability

Random Forests
- Ensemble of decision trees “randomly” constructed
- More accurate predictions and reduced error

Random Forests Prediction based on Decision Tree Theory
Why use Random Forest Prediction?

Advantages

- Excellent predictors
- Useful if relationship between inputs and outputs is unclear
- Captures non-linear and interaction behavior
- Handles qualitative data as well as missing values
- Relatively stable due to diversity in trees
- Can handle small population size with large number of predictors
- Lower generalization error than other methods
- Runtime very fast, commercial/open source software available

Disadvantages

- Not so easily interpreted
- Predicts a numeric value (cost) - Not a parametric equation (CER)

Versatile Black-box Approach
Application: Logistics Transport Cost Prediction

Objective

▪ Predict the shipping cost of products to help determine the best locations to manufacture them

Analysis Approach

▪ 1000’s of data points, messy, missing values, many potential predictors

▪ Initial Plan: Multivariate Regression
  ▪ Very cumbersome; required manual partitioning into suitable subsets

▪ Chosen method: Random Forest Prediction
  ▪ Limited data prep; automatic partitioning / different perspectives
  ▪ Very easy to implement, execute, and analyze

Random Forest Prediction facilitates logistics transport cost analysis
Logistics Transport Cost Prediction Model

Data Description

- Consists of 150K data points
- Automatically separated into two distinct data sets
  - Domestic with ~ 100K data points
  - International with ~ 50K data points

Potential Predictors

- Started with 20 potential predictors
- Reduced to 3 key predictors
  - Mode of transportation
  - Origin &/or Destination (country/state)
  - Bill weight

Random Forest Prediction for Big, Messy Data

Getty images credits: Mario Gutiérrez – delivery truck; Anucha Sirivansuwan: barge; hollydc: mailbox; oat autta: cargo truck; JPM: train
Analytical Results

Goodness of fit – Predicted $R^2$
- International: 0.83
- Domestic: 0.88

Graphical Interpretations
- Quickly produce various charts via R Shiny web-based application

Analysis made easy with R Shiny Package
Next Steps: What to do about the …

Decision makers want to know what’s inside

- What can we do?

Compare results to actuals …

- Using excel?  **Be Careful!**

Develop Interpretation GUI

- R-Shiny to peek inside the black box
- Visualize / Automate standard statistical analyses
- Ability to “play” with the model

Build algorithm to “create” a CER

- From all the trees, branches, values
- Cost prediction $\approx f(\text{tree}_i), \ i = (1..n)$

Provide ability to “peek” into black box
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Application: Analysis of Cost Saving Ideas

Objective

- Identify best cost savings ideas to apply to other products

Analysis Approach

- Collaborative workshops to generate ideas to optimize the product
- 1000’s of ideas in free form text from 100’s of workshops
  - Could any of these ideas be applicable to other products?
- Natural Language Processing to identify cost-savings ideas for reuse
- Chosen Methods: Latent Semantic Analysis, Latent Dirichlet Allocation
  - Powerful, well-proven, task-invariant algorithms
  - Framework already in place – Open source algorithms

Natural Language Processing Analyses highlight ideas for reuse
Generalize Cost Savings Ideas via Text Analytics

Collaborative Idea Generation

Review Product Detail

Generate Ideas: 10s

Aggregate ideas from 100s of products

1000s Unique Ideas

Machine Learning Analysis

Identify key terms

Group ideas into topics to generalize results

Heat map aligns product ideas to topics

Can we identify & apply Ideas from one product to others?
## Similarity Matrices to Align Ideas

### Unstructured Text

- 100s documents
- 1000s freeform “texts”

### Clustering Ideas

<table>
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<th>Product</th>
<th>Idea</th>
<th>Idea Id</th>
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<td>I-1</td>
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<td></td>
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<td>I-9</td>
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### Similarity Matrices

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Idea #1 from Product X highly similar to Idea #9 from Product Z

**Cluster similar ideas from unique products via similarity matrices**
Text Analytics to Identify Reusable Ideas (1 of 2)

Latent Semantic Analyses

Cluster similar ideas & identify key terms and main concept

Main Cost-Savings Idea

Reduce # of retention clips for installation of wires

Key Terms

coating, door, assembly, plate, material, housing, fasteners, cost, plate, cover, standard

Topic cluster

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Text Analytics to Identify Reusable Ideas (2 of 2)

Latent Dirichlet Allocation & Term Frequency – Inverse Document Frequency

Term frequency ~ importance ~ of idea aligned with product
Next Steps

Validate model and verify results

- Modify & Implement existing GUI Framework
- “Evaluate” results – requires thinking!

Scale to larger population

- Hundreds more workshops & products
- Thousands more ideas

Capture and incorporate actuals

*Implement cost-saving ideas on other products*
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Challenges for Cost Analysis Community

Machine Learning for cost analysis & estimating

- Different … from traditional methods
  - Will take time to catch on

- Black box method
  - Not so easy to interpret or follow input-to-output logic

- Regression Algorithms
  - Predict a numeric value (cost) - not a parametric equation (CER)

- ML Algorithms
  - Require pre and post processing for reasonable results

*Do Benefits outweigh Challenges?*
Authors

Karen Mourikas is an Associate Technical Fellow at The Boeing Company specializing in Operations Analysis, Affordability, and Systems Optimization. Her current work includes Product Teardown & Should-cost analyses, and Production Systems modeling. Karen has MS degrees in Applied Math and in Operations Research Engineering from the University of Southern California. Karen is a life-time member of ICEAA and has presented at several ICEAA & ISPA/SCEA conferences over the years.

Nile Hanov is a Data Scientist at Boeing Research & Technology where he develops novel next gen solutions for commercial and military platforms. In this role, he applies machine learning to event driven data to help organizations better understand and predict failures on board of an aircraft. Nile has four patents under review by the U.S. Patent Office all of which focus on event forecasting and system improvement. He is also currently pursuing a Ph.D. in Computer Science (with a focus on Artificial Intelligence and Machine Learning) at University of California - Irvine.

Joseph King is a data scientist at The Boeing Company with Boeing Commercial Airplane Analytics, utilizing data to build predictive models and provide analytical solutions. Joseph has contributed to areas such as sensor data analysis, text mining maintenance messages, and customer behavior modeling. Joseph’s education background includes a MS in Business Analytics from the University of Tennessee and a background in mathematics and operations research.

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Machine Learning & Non-Parametric Methods for Cost Analysis

The world of big data opens up new opportunities for ICEAA, such as machine learning and non-parametric methods. These methods are more flexible since they do not require explicit assumptions about the structure of the model. However, a large number of observations is needed in order to obtain accurate results. Hence, big data to the rescue! This presentation examines several non-parametric methods, with examples related to our community, and discusses opportunities and limitations going forward.
Questions?