When the Old meets the New: How Advanced Data Analytics is Transforming Manufacturing

Data Mining and Machine Learning at Bosch

Rumi Ghosh, Data Mining Services, Palo Alto, CA
Outline

- Introduction to Bosch
- Industry 4.0 and Automation in Manufacturing
- Role of Bosch in Industry 4.0
- Industry 4.0 and data analytics
- Data Mining and Big data analytics at Bosch
- Some success stories
- Barriers to progress
- The need for standardization
- PMML for standardization and Deployment
- Deployment and Scoring Engine Evaluation
- Conclusion
Bosch Sensor Tec – MEMS1

→ 50% of smartphones worldwide already use Bosch sensors.
No Car Without Bosch
Bosch Manufacturing

1000s of assembly lines

>250 Manufacturing facilities

billions Of parts manufactured each year

As of 01/2014
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Industry 4.0

1. industrial revolution
- **Mechanisation**
  - Mech. control (cam disc, cam)
  - Energy: water / steam power

2. industrial revolution
- **Electrification**
  - Punch cards as program memory
  - Conveyer belts
  - Master shafts
  - Energy: electrical

3. industrial revolution
- **Digitalization**
  - Freely programmable control units
  - PLC and PC based control units
  - Field bus (ethernet-based)
  - Flexible production systems
  - Digital data storage

4. industrial revolution
- **Connectivity and Traceability**
  - Usage of internet standards
  - Integrated IP-connection
  - Identifiable and communicating objects
  - Mobile operation
  - Scalable systems (cloud as storage, ..)
  - Self-optimising systems
  - Internet-of-things

The transformation of Industry 3.0 to Industry 4.0 (advanced manufacturing) occurs gradually
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Data science standards in manufacturing analytics

Two perspectives for Bosch on Industry 4.0

**LEAD PROVIDER**
System manufacturer view / production resource view

**LEAD OPERATOR**
Product manufacturer view / product view

**Big Data**

- Decentralised intelligence
- Machine models
- Software
- Value added networks

**Technology and solution supplier for OEMs and end users**

**First mover in the realisation of integrated concepts with equipment providers**

**Connectivity**

- Production models
- Business processes

**Value added networks**

**Software**
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The big data advantage in manufacturing

Source: http://www.mckinsey.com

1 Storage data by sector derived from IDC.
Where Does Analytics Add Value?

Data
- Structured
  - Internal
  - External
- Unstructured

Analytics
- Database Technologies
- Statistics & Optimization
- Artificial Intelligence
  - Machine Learning

Value
- New Revenue Streams
- Optimization / Eliminating Waste

Traditional
Data: structured, internal, relational
Query (SQL):
```
select *
from Item_Table
where price<2.00
```
Result

Data Mining
Heterogeneous data sets: structured & unstructured, internal & external
Query:
- Does behavior affect stroke risk?
Result
- Estrogen-containing birth control increases risk by 4%
- Regular apple & pear consumption decreases risk by 40%
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Our analytics information workflow

Modeling
- Extraction, Transformation, Loading
  - DB Connectors
  - Custom Scripts
- Aggregate Data
  - Hadoop
  - MongoDB
- Historic Training Data
- Analytics, Machine Learning
  - SAS
  - IBM SPSS
  - Python
  - Alpine
  - KNIME
  - R
  - RapidMiner
- Descriptive Analysis

Production
- Prognosis, Decision (-Support)
- Extraction, Transformation
- PMML

"Data at Rest"

"Data in Motion"

Sales Data
Production Data
Warranty Data
Device Data
## Data Mining Services

### How To?

| Business & Data Understanding | ➔ Business opportunities and Use case analysis  
|                               | ➔ Business impact analysis  
|                               | ➔ Data readiness assessment  |
| Data Preparation               | ➔ Data collection and organization  
|                               | ➔ Data cleaning  
|                               | ➔ Data integration  |
| Modeling & Evaluation           | ➔ Knowledge discovery  
|                               | ➔ Model building  |
| Model Deployment                | ➔ Onsite model deployment and calibration  
|                               | ➔ Offsite hosting of data collection & analytics solutions  |
| Maintenance                    | ➔ Data model updates due to process changes or new data  
|                               | ➔ HPC services  
|                               | ➔ Technology upgrades  |
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Analytics success stories in manufacturing

Test and Calibration Time Reduction
- Prediction of test results
- Prediction of calibration parameters

Scrap Costs Reduction
- Early prediction from process parameters
- Descriptive analytics for root-cause analysis

Warranty Cost Reduction
Prediction of field failures from
- Test and process data
- Cross-value stream analysis

Yield Improvement
- Benchmark analysis across lines and plants
- Pin-point possible root causes for performance bottlenecks (OEE, cycle time)

Predictive Maintenance
- Identify top failure causes
- Predict component failures to avoid unscheduled machine down-times
Use Case: Scrap Reduction

Business Objective
Reduce scrap by identifying top influential parameters

Data Sources & Analytics Approach

PRODUCT & DATA
- Assembly stations: >600 variables
- 6 end-of-line testing stations

METHODOLOGY
- Descriptive Analysis
  - Correlations
  - Scatter plots
  - Histograms
- Predictive Modeling
  - Regressions
  - Support Vector Machines
  - Decision trees
  - Decision rules

RESULTS

Result
- Sixteen variables identified as influential out of hundreds.
- Root cause analysis initiated.
- **Major cause of high scrap rate identified**
- We provided suggestions on adjustments of parameters and rules to design of conditions

Value
Scrap costs reduced by 65% of the baseline
Data Mining Services
Use Case: Test Time Reduction with HoP2

Business Objective
- Reduce test and calibration time in the production of mobile hydraulic pumps
- Pilot Product: load sensing control block SB23-EHS1

Data Sources & Analytics Approach
Stations PS22 and PS23 as bottleneck in production
Descriptive Analysis + Predictive Modeling
Modeling Results
- Correlations
- Dimensionality Reduction
- Group Lasso
- Random Forest
- Decision Trees

Result
- 41 secs saved, corresponding to **23% of total test time**
- Additional calibration time saved
- Additionally: development of **calibration toolbox**

Value
- **Cost savings** for forecast production volume in 2015
- Roll-out of solution to other products discussed

Also rolled out at BanP1, LoP2, RBCB
Test Time Reduction Tool

Use case
- End-of-line testing needs to be as effective as possible
- Only those test steps that are needed to ensure quality should be performed
- Reducing test time usually also increases production output and reduces capital expenditure

Target users
- Production planners: focusing on end-of-line testing
- Engineers: focusing on the implementation of testing processes

Goals
- Reduce test efforts without external support
- Concrete proposals for further improvement actions
- Web-based, user-friendly application of data analytics techniques

www.bosch-si.com/webinar-analytics-tools
Test Time Reduction Tool

Benefits from using the tool

- Solution guides users from data upload through definition of test steps to final results of analysis
- No assistance by data analytics team required
- Easy-to-access and -use web service without installation & training
- New improvement potential in terms of output and costs with respect to quality
- Solution proposals to reduce test efforts
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Data science standards in manufacturing analytics
The need for standards in predictive analytics

Bosch's interest in Standards for Manufacturing Analytics

As an user/operator
Vendor independence
Interoperability and Standardization of data collection, storage, retrieval, and presentation
Data-driven verification and validation for improving efficiency and quicker scaling
Use of best practices and standards to improve quality and traceability
Model auditing and update

As a provider
Interoperability and Standardization
Drive adoption of data-driven modeling, V&V
Sharing of success stories and best practices
Bosch is a leading participant in ASME’s initiative on verification and validation for advanced manufacturing
Creation of neutral testbeds and certification agencies
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Deployment and Scoring Engine Evaluation

Why use PMML

Shorter, low-overhead and low-complexity modeling

Clear separation between model development and deployment

Complete reproducibility of results across iterations

Open, encapsulated representation of statistical and data mining models and associated metadata
Data science standards in manufacturing analytics

Deployment using PMML

Model (Boosted Trees) developed in R
Implementation time ~1 month
Proposed a client-server architecture using the PMML implementation by ADAPA
No installation required at the client
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Deployment and Scoring Engine Evaluation
PMML Vendors (Producer & Consumer)
Deployment and Scoring Engine Evaluation

Evaluation Metrics – ISO/IEC 9126

Apply Software Evaluation Standard as basis of metrics (ISO/IEC 9126):

<table>
<thead>
<tr>
<th>SOFTWARE</th>
<th>CHARACTERISTIC</th>
<th>SUB CHARACTERISTICS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portability</td>
<td>Adaptability, Installability, Replaceability, Coexistence</td>
<td></td>
</tr>
<tr>
<td>Usability</td>
<td>Understandability, Learnability, Operability, Attractiveness</td>
<td></td>
</tr>
<tr>
<td>Functionality</td>
<td>Suitability, Accuracy, Interoperability, Security</td>
<td></td>
</tr>
<tr>
<td>Efficiency</td>
<td>Time behavior, Resource utilization</td>
<td></td>
</tr>
<tr>
<td>Reliability</td>
<td>Maturity, Fault tolerance, Recoverability, Reliability</td>
<td></td>
</tr>
<tr>
<td>Maintainability</td>
<td>Analyzability, Changeability, Stability, Testability</td>
<td></td>
</tr>
</tbody>
</table>

Score software in grades [1, 5] to levels [low, high]:

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Deployment and Scoring Engine Evaluation

PMML Vendors – Selection

Compatible with latest version of PMML 4.2 come out in 2014

Either/both producer (converter) or/and consumer (predictor)

Black box (source code) in generating PMML

Support Top 10 data mining models

Available (open source/license)
Deployment and Scoring Engine Evaluation

Efficiency

- Criteria
  - Efficiency
    - Resources utilization, Time behavior (limited access)
  - Functionality
    - Model Support, Platform Operability
  - Usability
    - Well-structured and documented modules, Helpful tutorial, operability
  - Maintainability
    - Customer support, User community
  - Reliability
    - Error handling (missing values, incorrect parameters), Recovery after crash
  - Portability
    - OS support, Installation/Un-installation directions, Installation Ease
Overall Scores

Score software in grades [1, 5] to levels [low, high]:

Means NOTHING without CONTEXT!
Data science standards in manufacturing analytics

Summary of first impressions in using PMML

- Vendor independence
- Freedom of development tools for the data scientist
- Each vendor implements PMML differently
  - Standardization of the PMML standard 😊
- PMML from all producers are not supported by all consumers
- Model coverage of most producers is limited
  - JPMML-SKlearn seems have maximum model coverage
  - Adapa had to be extended in our application; many thanks to Zementis for a quick response
- Error handling can potentially be improved
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The role of data mining in manufacturing starts much earlier than you may think

- Data mining is about asking the right questions.

- Insights from data come cheap, but a verification strategy can be expensive.

- To ask the right questions, collaboration with the domain experts is key.

- There is a need for standards in predictive analytics in manufacturing
Data science standards in manufacturing analytics

Join the manufacturing analytics community

Predictive Modeling in Manufacturing Analytics Challenge
Kaggle Competition to be launched on August 17th, 2016

Focus on improving product quality as a binary classification problem (0.6% in one class)
1 year of a product manufactured in large volumes and probably in your car
Complete assembly and testing data
3 million samples, 4000 features,

Public testbed for manufacturing data science innovation

IEEE Big Data for Advanced Manufacturing Special Symposium
2016 IEEE International Conference on Big Data
Dec 5 – Dec 8 2016 @Washington D.C., USA
http://cci.drexel.edu/bigdata/bigdata2016/SpecialSymposium.html

August 31, 2016: Results due for the manufacturing data challenge
Sept 20, 2016: Due date for full symposium papers submission
THANK YOU

Carlos Cunha, Data Mining Services, Palo Alto, CA
The role of data mining in manufacturing starts much earlier than you may think

- **Data mining is about asking the right questions.** But knowing what are the right questions is hard, even for the best practitioners. The next best thing is to be able to answer questions fast, and setting up data collection that will enable those to be answered. You also have to anticipate that new issues will arise. The infrastructure has to enable rapid access to new data to solve the new questions.

- **Insights from data come cheap, but a verification strategy can be expensive.** (It’s easy to identify top features using machine learning, but testing them out on the assembly line is not so easy).

- To ask the right questions, **collaboration with the domain experts is key.** But for that collaboration to work, domain experts need training in data mining and the correct incentives.

- There is a need for standards in predictive analytics in manufacturing.
Real world data mining

▶ Taking some data and fitting it to a model is easy.

▶ Dealing with people is a different skill set.

- Who is pushing for data mining in that plant?
- How to engage the domain experts? And keep them engaged?
- How to turn data mining analysis into actionable insights that the plant will accept?
Use Case: Yield Improvement / Anomaly Detection

**Business Objective**

Reduction of scrap in production

**Data Sources & Analytics Approach**

1. Validation and extension of current 6 sigma analysis
2. Development of reusable Tableau tool for on-site analysis

**Result**

- **Tool available** enabling comprehensive descriptive data investigation (daily parameter values, histograms (in 2D), correlations, failure modes, ...)

**Value**

$\boldsymbol{\text{Effective identification of root cause when problem occurs at the line.}}$
Use Case: Performance anomalies detection

<table>
<thead>
<tr>
<th>Business Objective</th>
<th>Comparison of multiple worldwide assembly lines and identification of slow lines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Sources &amp; Analytics Approach</td>
<td><img src="image" alt="Diagram of data flow" /></td>
</tr>
<tr>
<td>Data</td>
<td>Analysis</td>
</tr>
<tr>
<td>Manufacturing Execution System</td>
<td>Production Data</td>
</tr>
<tr>
<td>Data linked over worldwide lines / processes / stations</td>
<td></td>
</tr>
<tr>
<td>Result</td>
<td>Tool developed as dashboard where users can discover and compare line performances interactively</td>
</tr>
<tr>
<td>Value</td>
<td>Data integration across different plants enabled, higher transparency by comparison with benchmark line, technical feasibility of real-time analysis of live and historic data created.</td>
</tr>
</tbody>
</table>
Deployment and Scoring Engine Evaluation

Efficiency

- **Criteria**
  - Resources utilization
  - Time behavior (limited access)

- **Comments**
  - Py2PMML exports dot file for each tree
  - JPMML-Sklearn dumps pickle file for each model
  - JPMML-Evaluator and Kamanja consume time for IO files
Deployment and Scoring Engine Evaluation

Functionality

Criteria
- Model support
- Platform interoperability

Comments
- Py2PMML, sklearn_pmml and KNIME converter support limited models
- Kamanja returns predicted class only for classifier
- KNIME predictor is interoperable only with PMML generated by R/Rattle, KNIME
Deployment and Scoring Engine Evaluation

Usability

Criteria
- Well-structured and documented modules
- Helpful tutorial
- Handy operability

Comments
- sklearn_pmml provides insufficient comments in source code and no tutorial
- Kamanja runs on Kafka and Zookeeper with complex configurations
Deployment and Scoring Engine Evaluation

Maintainability

- **Criteria**
  - Customer support
  - User community

- **Comments**
  - sklearn_pmml offers no technical support
Deployment and Scoring Engine Evaluation

Reliability

- **Criteria**
  - Error handling (missing values, incorrect parameters)
  - Recovery after crash

- **Comments**
  - sklearn_pmml handles all missing and invalid values with treatment of “asIs”
  - Openscoring software and Kamanja lack missing or invalid values treatment, fail conversion by throwing exception
  - KNIME skips missing values, replaces invalid values
Deployment and Scoring Engine Evaluation

Portability

Criteria

- OS support
- Installation/Un-installation directions
- Installation Difficulty

Comments

- All software except Kamanja are compatible with common OS (Windows, MacOS, Linux)
- Py2PMML replies on Apache-Tomcat REST service (run as Administrator)
- sklearn_pmml requires PyXB, provides poor installation directions
- Openscoring software relies on Java, maven (proxy setting), no official installation directions
Deployment and Scoring Engine Evaluation

What is PMML

- Predictive Model Markup Language
- Data mining standard (DMG)
- XML configuration file
- Development & Deployment
Agenda

1. What is and why use PMML – Standard & Production

2. PMML Producer – Py2PMML & Max & Openscoring & KNIME

3. PMML Consumer – ADAPA & Openscoring & Kamanja & KNIME

Deployment and Scoring Engine Evaluation

What is PMML

- Predictive Model Markup Language
- Data mining standard (DMG)
- XML configuration file
- Development & Deployment
Data science standards in manufacturing analytics

How to improve existing standards?

Certification of compliance by DMG

Keep up with the innovation in modeling paradigms

Standards have to cover the complete analytical workflow

ETL

Model creation

Model deployment

Validation

Interpretation and uncertainty quantification

Versioning and traceability

Consideration of development and deployment environments
Barriers to rapid progress

- Flexibility is viewed as anathema to efficiency
  - Scale and repetition as a driver of quality and efficiency
- The skills gap: Industry 4.0 workforce will need abundant STEM skills
- Significant investment in infrastructure needed
  - New sensors, connectivity, data collection and computing platform, and machinery
  - Longer ROI a barrier to VC investment
- Data in silos
  - Data not viewed as an asset: Data collection driven by regulatory fear
  - Suppliers, OEMs, and users unwilling to share data
- Lack of standardization
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  - Sharing of success stories and best practices: Bosch is a leading participant in ASME’s initiative on verification and validation for advanced manufacturing
- Energy and labor policies are constantly changing
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Drive and Control Technology Division

Mobile applications
- Construction machinery
- Materials handling
- Agricultural and forestry machinery
- Commercial and road vehicles

Machinery applications and engineering
- Industrial equipment
- Marine and offshore
- Bulk materials handling

Factory automation
- Machine tools and automotive
- Assembly and handling, semi-conductors, and solar
- Food, packaging and printing

Renewable energy
- Wind power
- Marine power

Mobile Applications business unit

Industrial Applications business unit

Renewable Energies business unit

1 Bosch Rexroth AG (100 % Bosch-owned)
Bosch Packaging Technology is the leading supplier of turnkey solutions for packaging and process technology

(1) Bosch Automation
Consumer Goods – Power Tools

- **Hand-held power tools**: World market leader for DIY and professional tools
- **Benchtop tools**: Innovative tools for woodworking and metalworking
- **Accessories**: Global leader with more than 100,000 accessory parts
- **Garden tools**: Innovation driver for garden tools
- **Measuring tools**: Precision tools for professional and DIY users
The product portfolio of the Bosch Home Appliances division covers the entire range of modern household appliances.
Security Systems Division

Product business

Systems and products for safety and security

Building security

Customized building security with total customer support

Communication Center

Services in the areas of security and communications
### Deployment and Scoring Engine Evaluation

#### Conclusions & Recommendations

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<th>KNIME</th>
</tr>
</thead>
<tbody>
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<td>Efficiency</td>
<td>6</td>
<td>8</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>Functionality</td>
<td>5</td>
<td>3</td>
<td>10</td>
<td>5</td>
</tr>
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**Means NOTHING without CONTEXT!**
### Deployment and Scoring Engine Evaluation

Conclusions & Recommendations (cont.)

**Means NOTHING without CONTEXT!**

#### PMML Consumer Evaluation Scores

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**Evaluation Scores (higher is better)**

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