Machine learning strikes from below, a mining application:

Material Classification by Drilling

Input
Drilling measurements
Penetration rate
Specific energy

Neural network
Classifier

Output
STRENGTH INDEX CLASS
DEPTH, cm

Strong
Weak

Machine Learning 2005
Johan Larsson
Papers

Material Classification by Drilling
Diana LaBelle, John Bares, Illah Nourbakhsh
Robotics Institute, Carnegie Mellon University

Neural Network Technology for Strata Strength Characterisation
Walter K. Utt, Spokane Research Laboratory
National Institute for Occupational Safety and Health
Outline

Introduction
Extraction method
Experimental setup
Data processing, network training
Results
Why material classification by drilling?

Because we want to limit the hazards of working in a mine.
Mine statistics (USA)

- In 2003, there were 56 occupational mining fatalities, compared to 66 in 2002.
- In 2003, 16 occupational mining fatalities occurred in underground work locations.
- The underground work location fatality rate was 35.7 per 100,000 FTE workers.
- Of the underground fatalities, 11 occurred in coal operator mines, 4 among coal contractors, and 1 in a stone operator mine.
- Coal contractors had the highest fatality rate (212.8 per 100,000 FTE employees), followed by stone operator employees (54.1) and coal operator employees (32.0).
Coal mine facts (USA)

- The failure of structural supports accounts for approximately 400 injuries and 10 deaths each year.
- Over half of the most recent fatalities have occurred under supported roof.
- Main problems are roof falls and rock bursts.

Lackawanna Coal Mine, Pennsylvania
Why is coal mining more dangerous than ore mining?
Extraction method
Limited information about lithology of surrounding rock

Better knowledge of the lithology of the surrounding rock

- augmented ground control plans
- more effective bolting
- alert miners of local hazards

improved safety
How lithological information is attained today

- Exploratory drilling
- Pre mining
- Expensive => sparsely used
- Core log gives limited information
- Drill cores miss local geologic anomalies
- The mining process changes the structural conditions
Current and previously explored hazard detectors

Currently used reactive detectors
- Miners
- Extensometers

Currently used pro-active detectors
- Gas detectors

Previously explored pro-active detectors
- Ground penetrating radar
- Ultrasonic sensors
- Instrumented roof bolts
Bolting

- Common method for roof and rib support today
  - Does not require extra space
  - Dependent on something to “hang on to”
- Different types and lengths
Outline of papers

Diagram:
- Sensor 1
- Sensor n
- MUX ADC LPF
- Computer controlled data acquisition
- Drill
- Conversion to features

Table:
<table>
<thead>
<tr>
<th>Input</th>
<th>Neural network</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drilling measurements</td>
<td>Classifier</td>
<td>Class of rock strength (0-31)</td>
</tr>
<tr>
<td>Penetration rate</td>
<td></td>
<td>Strong rock (8-31)</td>
</tr>
<tr>
<td>Specific energy</td>
<td></td>
<td>Medium strength rock (4-7)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Weak rock (1-3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Very weak seams, fractures, voids (0)</td>
</tr>
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</table>
Previous work in rotary drill parameter analysis

- Scoble et al, “Drill Monitoring Investigations in a Western Canadian Surface Coal Mine.”
- King and Siegner, “Using Artificial Neural Networks for Feature Detection in Coal Mine Roofs.”
Specific Energy of Drilling (SED)

SED is the drilling energy input or work done per unit volume of rock excavated.

- Acceptable to use when estimating relative strength between layers
  + Easy to use
  - Depends on how finely the rock is ground at the drill bit
  - Strong fractured material appear as weaker solid material
Approach

- Use data from an instrumented mine drill to classify a small set of materials that are typically found around a coal seam
- In real time without an operator to perform classification
- Classification independent of drill operator or drill conditions

Motivation:
- Drill response correlates to the properties of the material being drilled
- Properties as abrasiveness, hardness, and (compressive) strength directly affect the drilling process
Approach

- Drilling process complicated to model
- Large number of variables influencing drill process
- Relationships between these dynamic variables are not well-understood or even known

Drilling application is a good candidate for machine learning

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Experiments

- Evaluate possibilities to use a Neural Network for real time classification of the properties of the material being drilled
- More specific, discriminate between concrete layers in a test block
- Concrete test block in five layers

<table>
<thead>
<tr>
<th>Layer</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concrete Mix</td>
<td>Grout</td>
<td>Limestone</td>
<td>Fly-ash</td>
<td>H.E.S</td>
<td>H.E.S</td>
</tr>
<tr>
<td>Comp. Str. (psi)</td>
<td>1,900</td>
<td>5,600</td>
<td>1,300</td>
<td>4,500</td>
<td>4,300</td>
</tr>
<tr>
<td>Thickness (in)</td>
<td>11</td>
<td>5</td>
<td>9</td>
<td>4</td>
<td>7</td>
</tr>
</tbody>
</table>

Table 1. Concrete Test Block Characteristics (H.E.S. is High Early Strength concrete)
Experimental setup
Experimental setup

Recorded parameters:

Exclusively for experiment
• Torque
• Thrust
• Rotary speed

Standard drill parameters
• Drill bit position
• Rotary pressures
• Thrust pressures
Data collection:
- 40 holes in a rough grid pattern
- Average 90 s to drill a hole
- Typical data file between 60000 and 100000 data points
- Each with seven (eight) real valued sensor readings
Data processing

- Calculate penetration rate
- Each file is sub-sampled by 1%
- Choosing data points from clean segments (avoiding transitions between layers)
- Normalized over range of sensor values
- Calculating virtual sensors
- Each segment is collapsed into one single data point
Data processing

Virtual sensors

- Not a physical sensors, but functions of the drill’s sensors
- Represent complex relationships between drill behavior and material properties
- The information from the virtual sensor is another drill parameter and another variable for a neural network to use

Virtual sensors
- Std. Dev. Thrust
- Std. Dev. Torque
- Std. Dev. Penetration
- Std. Dev. Thrust Diff
- Std. Dev. Rotary Diff
Neural Network

Network with no hidden units tested, averaged 80% classification error => non linear realationships

- Two layer feed forward
- Four hidden nodes
- Backpropagation
Twelve experiments conducted
1) All real and virtual
2) All real without redundancy
3) As 2) but thrust excluded
4) As 2) but torque excluded
5) As 2) but RPM excluded
6) As 2) but penetration rate excluded
7) Only real drill sensors
8) Drill sensors and virtual drill sensors
10) - 12) Only one parameter used

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Experiment</th>
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<tr>
<td></td>
<td>1</td>
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<tr>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td>Thrust (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Torque (p)</td>
<td>✓</td>
</tr>
<tr>
<td>RPM (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Penetration (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Rotary In (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Rotary Out (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Thrust In (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Thrust Out (p)</td>
<td>✓</td>
</tr>
<tr>
<td>Thrust Diff. (v)</td>
<td>✓</td>
</tr>
<tr>
<td>Rotary Diff. (v)</td>
<td>✓</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>✓</td>
</tr>
</tbody>
</table>
For each of the twelve experiments, 11 randomly chosen files out of 14 is used for training, the other 3 is used for testing.
Experimental Results

- Best performance 4.5% average error shows that drill parameters can be used for material classification.
- Thrust and torque are the most critical in discriminating between the materials (3 - 6).
- The usage of virtual sensors significantly increases the NN:s ability to classify materials correctly (1-2 and 7-8).
- All of the parameters thrust, torque, rpm or penetration rate equally poor at classifying materials 4 and 5.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Error Rates by Material (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>4.2</td>
</tr>
<tr>
<td>3</td>
<td>48.9</td>
</tr>
<tr>
<td>4</td>
<td>12.7</td>
</tr>
<tr>
<td>5</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>0.1</td>
</tr>
<tr>
<td>7</td>
<td>44.8</td>
</tr>
<tr>
<td>8</td>
<td>0.0</td>
</tr>
<tr>
<td>9</td>
<td>14.0</td>
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<tr>
<td>10</td>
<td>57.6</td>
</tr>
<tr>
<td>11</td>
<td>76.8</td>
</tr>
<tr>
<td>12</td>
<td>54.8</td>
</tr>
</tbody>
</table>
Experimental Results
Learning rate

- Improves until approx. 90 iterations
- Material 5 consistently has highest error rates
Additional reading


Schunnesson, H., 1997 Drill process monitoring in percussive drilling for location of structural features, lithological boundaries and rock properties, and for drill productivity evaluation.