Responding to the AI Challenge
Learning from Physical Industries

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How can other industries inform AI in finance?

- Four learnings from outside of finance
- Three areas of exploration
- Two quick MATLAB PSAs (public service announcements)

AI in this talk includes;
machine learning, deep learning, reinforcement learning…
Our Customers / Key Industries

Aerospace and Defense  Automotive  Biological Sciences  Biotech and Pharmaceutical  Communications

Electronics  Energy Production  Financial Services  Industrial Machinery  Medical Devices

Process Industries  Neuroscience  Railway Systems  Semiconductors  Software and Internet
Four Learnings from Other Industries

1. Plenty of value away from the “obvious” applications
2. There’s no reason not to look for your keys under the street light: If you have data use it
3. Regulations can be tough – but perhaps not for advice.
4. If you don’t have data, can you create it?
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Society of Automotive Engineers
Levels of Autonomous Vehicles
Subaru (a customer)

**Advanced Driver-Assistance Systems**

*Critical safety features* for everyone

Detects obstacles, applies brakes, adjusts cruise control, and stays in lane
BMW - Machine Learning to Detect Oversteering

“With little previous experience with machine learning, we completed a working ECU prototype capable of detecting oversteering in just three weeks.” Tobias Freudling, BMW Group

- Engineers gathering and cleaned data
- Explored many machine learning approaches with Classification Learner App
- Generated code for vehicles on test track

Link to technical article
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Detect Abnormalities

Musashi Seimitsu Industry Co., Ltd.

Automated visual inspection of 1.3 million bevel gear per month

Manufacturers often have a trove of labelled data
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Genentech
Deep Convolutional Neural Networks for Digital Pathology Analysis

Generate training data iteratively
- Model is iteratively improved by adding more data
- Removes need to annotate tumor by hand

Segment tumor tissue from necrosis
- Segmentation of massive 25k x 25k images
- Trained and deployed U-Net semantic segmentation algorithm

Green = tumor
Red = necrosis
Blue = other

Not a diagnosis! Assists pathologist
MATLAB PSA #1
Use the **Live Editor** to create scripts that combine code, output, and formatted text in an executable notebook.
Now integrated with Symbolic Math Toolbox

Symbolic and Numeric in one Live Editor Notebook
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Predictive Maintenance: Reciprocating Pump

Predict pump failures in real-time using sensor data

“I keep my machines healthy and running so how do I get failure data to train a model?”
Generate Data

Obtain sensor data

Sensor Data

Build model

Simulink Model

Fine tune model

Inject Failures

Run simulations

Generated Failure Data

Incorporate failure modes

Sensor Data -→ Build model -→ Fine tune model -→ Inject Failures -→ Generated Failure Data -→ Run simulations
Preprocess Data

Data Preprocessing Methods
- Time Domain
- Frequency Domain
- Time-Frequency Domain

Failure Data (Sensors/Simulation)

Preprocessed Data
Feature Extraction & Condition Monitoring

### Feature Extraction Methods
- Order/Modal Analysis
- Time-Frequency Analysis
- Input-Output Models
- Model Coefficients & States
- Residual Generation
- ...

![Preprocessed Data](image1)

![Health Indicators](image2)

![Frequency Peaks](image3)
Predictive Model Training

Predictive Methods
- Anomaly Detection
- Fault Classification
- Remaining Useful Life
- Trending
- Hazard Distributions
- Time series Forecasting
- ...

Health Indicators

Frequency Peaks

Remaining Useful Life = 43.4 days

0 Days to Failure

100 Days to Failure
Three Topics to Watch
Three Topics to Watch

#3 Fragmentation in Hardware Architecture? (for Deep Learning)
Fragmentation in Hardware Architecture?

- NVIDIA is the standard for data-center deep learning
- But there are challengers;
  - FPGA from Xilinx, Intel, others
  - AMD Radeon
  - Google’s TPU
  - Embedded processors from ST, TI, Renasas, Infineon
- Over $1B of venture investment in AI chip startups
- Cloud is an accelerator
- Training vs. Inference
GPU falling out of favor as hardware for embedded deployment?

Edge computing hardware zoo:
- **Intel Neural Compute Stick 2** (left, top)
- **Movidus Neural Compute Stick** (left, bottom)
- **NVIDIA Jetson Nano** (middle, top)
- **Raspberry Pi 3, Model B+** (middle, bottom)
- **Coral USB Accelerator** (right, top) Google TPU
- **Coral Dev Board** (right, bottom) Google TPU

Image courtesy of Dr. Allasdair Allan
If multiple architectures become viable, then what?

- Evaluate HW for purpose – choose target
- Develop in high level language
- Transform to target executable
- A small number of finance customers doing this today (GPU, FPGA). Will this grow?
MATLAB PSA #2
Run MATLAB code faster with redesigned execution engine.

- All MATLAB code is now JIT compiled

- Incremental improvements each release
  - Faster assignment into large `table`, `datetime`, `duration`, and `calendarDuration` arrays
  - Construct objects and set properties faster
  - Render plots with large numbers of markers faster using less memory
  - Increased speed of MATLAB startup
Three Topics to Watch

#3 Fragmentation in Hardware Architecture? (for Deep Learning)

#2 Reinforcement Learning
Reinforcement Learning in the News Focuses Mainly On…

- Board Games
  - Chess
  - Go
- Video Games
  - Atari
  - DoTA, Starcraft
- Recommendation Systems

Posterior Sampling for Large Scale Reinforcement Learning

Nov 21, 2017

Posterior sampling for reinforcement learning (PSRL) is a popular algorithm for learning to control an unknown Markov decision process (MDP). PSRL maintains a distribution over MDP parameters and in an episodic fashion samples MDP parameters, computes the optimal...
…But Increasingly Being Seen In Context of Autonomous Systems

- Learn Complex Tasks
  - Manipulation
  - Planning
  - Navigation
  - Control
Traditional “Controls” Customers Have Proactively Engaged
100+ customers have spoken to us about Reinforcement Learning since 2018

- Reinforcement learning needs a lot of data, usually generated from models
- Models can incorporate conditions hard to emulate in the real world
- Many of them have MATLAB and Simulink models that can be reused
Using Reinforcement Learning to Improve Driving Control

Models like this are used by our customers to develop controllers and other algorithms.
RL for Autonomous Driving – Co-simulating with Unreal Engine
Project With A Major Automotive Company

- Step 1: Trained deep neural network (DNN) based driver
- Step 2: Use RL to improve performance of DNN-based driver
- Step 3: Use improved DNN to augment traditional controller
- Result: 2+ sec (7%) faster than the original driver
RL Interest Growing in Finance

- Notably JP Morgan LOXM (Limit Order Execution Management)
- Positive results for our first experiments
  - Stock trading
  - Hedging
- Academic activity – mostly automated trading
- Petter Kolm from NYU speaking later;
  - Dynamic Replication and Hedging: A Reinforcement Learning Approach
Three Topics to Watch

#3 Fragmentation in Hardware Architecture? (for Deep Learning)

#2 Reinforcement Learning

#1 Explainability and V&V for AI
Explainability in Finance: Principles of fairness require being able to explain why the model is making decisions

2. Use of personal attributes as input factors for AIDA-driven decisions is justified.

4. AIDA-driven decisions are regularly reviewed so that models behave as designed and intended.

8. Firms using AIDA are accountable for both internally developed and externally sourced AIDA models.

13. Data subjects are provided, upon request, clear explanations on what data is used to make AIDA-driven decisions about the data subject and how the data affects the decision.

Trade-off between predictive power and explainability

Explainable models

- Naïve Bayes Classifier
- Logistic Regression
- Decision Trees
- Shallow Neural Networks
- Random Forests
- Boosted Trees
- Deep Neural Networks

Simplicity

Classical Machine Learning

Increasing Predictive Power

Ensemble methods

Large quantities of data
Automated feature extraction

Scoring Rules
Attribution Reveals the Why Behind Deep Learning Decisions

Classified as “keyboard” due in part to the presence of the mouse

Incorrectly classified “coffee mug” as “buckle” due to the watch

Across Industries there are different meanings for…

Verification & Validation for AI

**EXPLAINABILITY**
Can you explain the working of AI model in human-understandable terms?

**INTERPRETABILITY**
Can you observe and trace cause and effect in an AI model and explain the rationale of the decision?

**ROBUSTNESS**
Is AI system immune from spoofing and other common attacks?

**DATA PRIVACY**
Can an attacker deduce sensitive training data from output of AI model or system?

**RIGOR & TRUST**
Has AI system been developed with defined, traceable and rigorous process?

**SAFETY CERTIFICATION**
Has AI system been developed with safety lifecycle as key component.
Common safety practices

- **Redundancy**: Redundant implementation with voting
- **FMEA**: Failure mode analysis to ensure safe behavior in anticipated scenarios
- **Monitoring**: Monitoring and logging to record decisions for post-mortem analysis
- **Auditing**: Audit trails of development activities
- **Data Separation**: Firewalls between training and test/validation data to ensure appropriate accuracy metrics are computed
- **Best Practices**: Documentation of best practices being followed to improve repeatability
Safety Standards Updates:
Very Early Phase

- **TUV SUD**
  - Open GENESIS
  - Started in May 2019

- **SAE and EUROCAE**
  - Joint Working Group WG-114
  - Kick-off in August 2019

- **RTCA (Aerospace, US)**
  - Still evaluating member’s interests

- **ISO JTC 1/SC 42**
  - Standardization program on Artificial Intelligence
  - In “Preparatory” phase – work not yet started
When designing physical products

- Modeling & Simulation
- Test & Verification
- Code Generation
Much of the process may be regulated
Connected Systems Means…

Discover, Prototype, Model, Simulate

Generate Code, Deploy

Test & Verify

Operation

Design

Operate
Positive improvements from field data

V.next

Design

Discover, Prototype, Model, Simulate

Test & Verify

Generate Code, Deploy

Operation

Operate

[Diagram showing various components and sensors related to wind turbine monitoring, such as Accelerometer, Bearing, Pressure, Temperature, Gearbox Oil, Gearbox Oil Level, Transformer, and more.]
Model Risk Management – The Model is the Product

- Emphasis on
  - Process
  - People
  - Inventory of Assets
  - Execution Phase
  - Reporting

- Learn more

A Platform for Risk Models
Paul Peeling, MathWorks

- Model developers, quants, analysts.
- Business lines
- Independent model review and audit
- Regulator
- Model Owners
- Risk management
- Board and stakeholders
- Regulator

SLOD
FLOD
“Explainability” More than SHAPley and LIME

- ...and Partial Dependency Plots and ... this is an active area of research

- The basics apply:
  - What is the quality and relevance of the data used to train the model?
  - Has the process to develop the model been recorded properly? (How was the data cleaned? What were the parameters used for training?)
  - How will the model be monitored in use?

- Anecdotally, customers have been able to explain models and methods sufficiently to allow use, when they have followed good practices.
  - Talk with our consultants if you need help with this
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Three Areas to Watch

1. If your application is performance dependent; Hardware Options
2. Reinforcement Learning is developing quickly, time to investigate?
3. AI regulations are here and coming; good practices are important