Improving Model and Data Governance With Auto-Encoder Self-Diagnostic Model

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Brief Introduction: FICO Analytics

- **Banking**: More Than Half of the top 100 Banks Globally
- **Insurance**: Two Thirds of the top US P&C Insurers
- **Retail**: One Third of the top US Retailers
- **Healthcare**: Four Fifths of the top Pharmaceutical Companies
- **Government**: Over 100 Government Agencies
Agenda

Introduction

Auto-Encoder Theory

Applications
- Monitoring supervised models with Auto-Encoder
- Monitoring unsupervised models with Auto-Encoder

Conclusion
Building Predictive Models

- **Supervised**: Correct classification provided

- **Unsupervised**: Model the data distribution (without labels)

Clustering and parametric estimate
Models must be designed to perform on data not seen.

- Typically done through splitting data into **testing** and **training**.
### Model Governance

Production *will be different*, out-of-time data

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**Governance** = Confidence that model will make good predictions on future data
Classic Data Governance - Data Quality Reporting

- Predictive models need high-quality data
- **Check** basic data integrity
  - **Data quality reports**
  - Red flags: Missing records, fields, or incorrect data types – numeric, date, categorical (missing/extra values)
- Monitor before and during model deployment
  - Data Statistics
  - Score Distributions
  - Model Performance snapshots
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- Monitoring Consortium Clients with Auto-Encoder
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Conclusion
Auto-Encoder rooted in Neural Networks

- Model inputs created or extracted from raw transaction data
- Each unit “neuron” is a computational unit that takes input and generate an output through an activation function
- Learn connections weights with supervised backpropagation algorithm

Activation function

\[ f(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \]
Auto-Encoder Learn a Data Representation

- Auto-Encoder sets target values to be equal to the inputs and apply unsupervised learning to minimize the reconstruction error.

- Once the auto-encoder has been learned, it provides a compressed distributed representation (encoding) of original data.

- The hidden units are latent representations of features.
Auto-Encoder Learning

- Auto-Encoder network is trained to output the input (learn identify function) $x_R(\theta) \approx x$

- Sparsity regularization (Kullback-Leibler (KL) divergence) on hidden nodes constrain activations to learn compact representation

$$\hat{h}_j = \frac{1}{m} \sum_{i=1}^{m} f_{h_j}(x_i) : \text{m training examples}$$

$$\min_{\theta} \|x_i - \hat{x}_i(\theta)\| + \gamma \sum_{j=1}^{w} KL(h_j^0||\hat{h}_j) : h \text{ a small constant}$$
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Production Falcon Models

*** Encoders are learned from training data ***
Terabytes of Client Contributed transaction data

- Statistical analysis often too generic to point to data integrity issues
- Auto-Encoder can easily identify sets of transactions across clients with different reconstruction errors which draw to the key data integrity issues
Anomaly inspector clustering module

Cluster Client’s large auto-encoder reconstruction errors

- Clusters point to root causes of large reconstruction issues
  - EX: shift in transaction amounts for Kazakhstan from one issuer
  - Allows data aspects to be fixed, model outcome minimized, rules created
Variables will often deal with data quality issues, may not use all data, or generalize in such a way that it can compensate for data.

In production monitoring you need to auto-encode the model inputs to determine when the inputs are not what the model learned.

Interactions can be captured through latent representation.
Latent feature visualization

- Hidden node visualization over data inputs can provide insight information about feature changes over time.
- Following example visual change in one hidden node is actually reflecting problematic profile variables and lower performance.

![Normal Data Visual](image1)

![Data Visual with Issue](image2)

![Performance impact](image3)
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Why Self-Learning Models?

► New emerging markets require flexible analytics

► Data availability issue
  ► Data export restrictions or limited data contributions
  ► Low quality data feeds / No historical data
  ► Unreliable fraud reporting/tagging

► Constantly changing customer behaviors and production environment
  ► Traditional models would degrade in an unacceptable fashion
  ► Regional differences exist in customer behavior / fraud patterns
Cyber Analytics Unsupervised Model

* Requestor IP: Internal computer’s IP
** Resolved IP: External host’s IP

DNS
Netflow
Web Log
DHCP

Requestor IP*
Resolved IP**
Requestor IP* + Domain name
Domain name

Adaptive Analytics
Archetype Update
Belief Propagation
Clique Analysis

Review Threshold
Case Review

U.S. Patent 8,027,439; 8,041,597; 13/367,344; 14/149,598
Monitoring unsupervised models

- Learning a companion auto-encoder network based on the same data as the unsupervised model.
- Unsupervised model and the auto-encoder network is packaged together and installed in the production environment.
- It monitors the reconstruction error regularly and calculate the reconstruction error in batch mode.
- It is necessary to occasionally redesign and rebuild the model when significant environmental changes reflected in the data.
Reconstruction errors in unsupervised model

- Track reconstruction error in production over time
- There can be constant evolving customer behaviors and fraud patterns
- When auto-encoder identifies significant environmental changes, it is necessary to redesign and rebuild the model
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Auto-Encoder Theory

Applications
- Consortium Data Diagnostics with Auto-Encoder
- Monitoring Consortium Clients with Auto-Encoder
- Choosing models for new Data
- Monitoring unsupervised models with Auto-Encoder

Conclusion
**Autoencoders: Detecting Integrity Issues**

*Abnormal patterns cannot be reconstructed as accurately*

Reconstructed input

Hidden layer

Anomaly input

Large Difference $\rightarrow$ **novelty**

Autoencoders: Detecting Integrity Issues

**Abnormal pattern**

Energy industry: Machine failure prediction

Reconstructed input

Hidden layer

Anomaly input

Catch the anomaly before it's out of control!

Large Difference in novelty

Thank You

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