FICO AML Advanced Analytics

Tackling Compliance Challenges with Explainable AI

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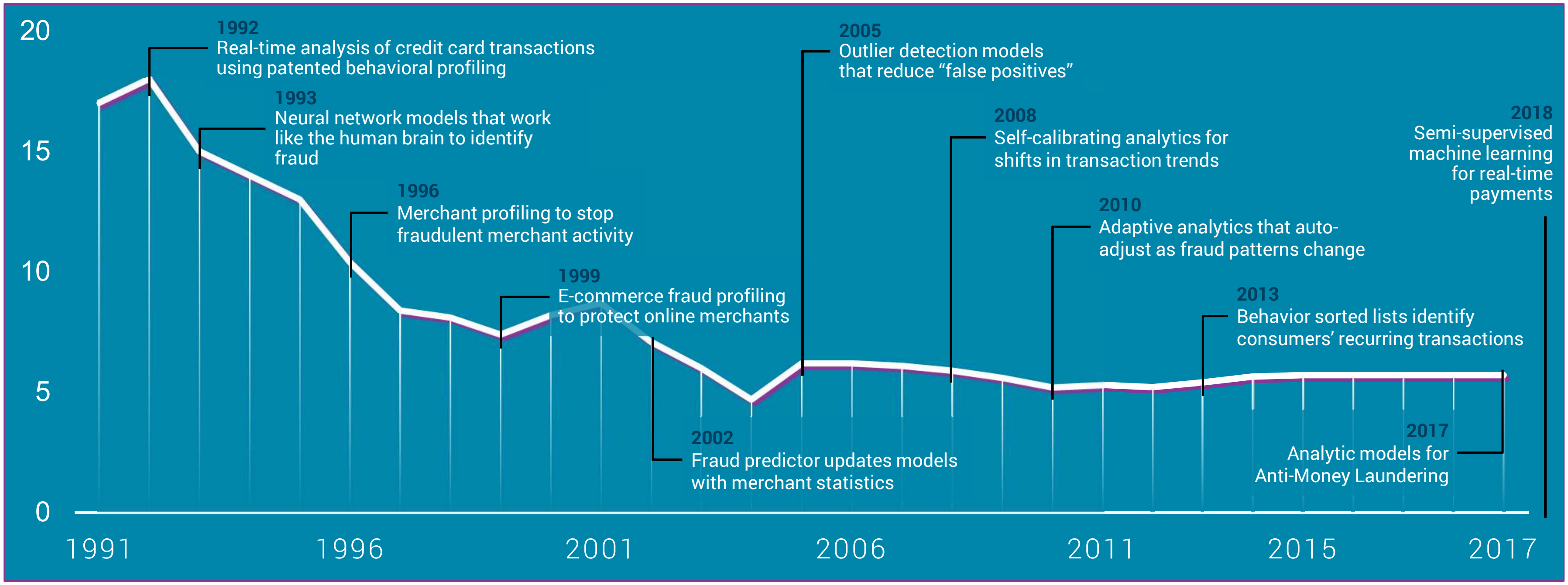
Leading innovation in fraud and financial crime prevention



194 patents granted, 91patents pending

FICO AML Advanced Analytics

Two scores are developed: Use together or independently. Scores from 1-999

AML Threat Score (Supervised)

Low Score
→ Unlike historical **SARs**
→ Normal peer-group behavior

High Score
→ Like historical **SARs**
→ Money-laundering suspected

Reason Codes: explain why model produced this score

- Detect suspicious behavior based on previous SARs
- Prioritize alerts to improve efficiency - Identify which alerts are more critical and investigate first
- Historical SARs data required to train model

AML Soft Clustering Misalignment Score (Unsupervised)

Low Score
→ Normal-behavior
→ Lower risk

High Score
→ Abnormal-behavior
→ Higher risk / Revisit KYC

Reason Codes: explain why model produced this score

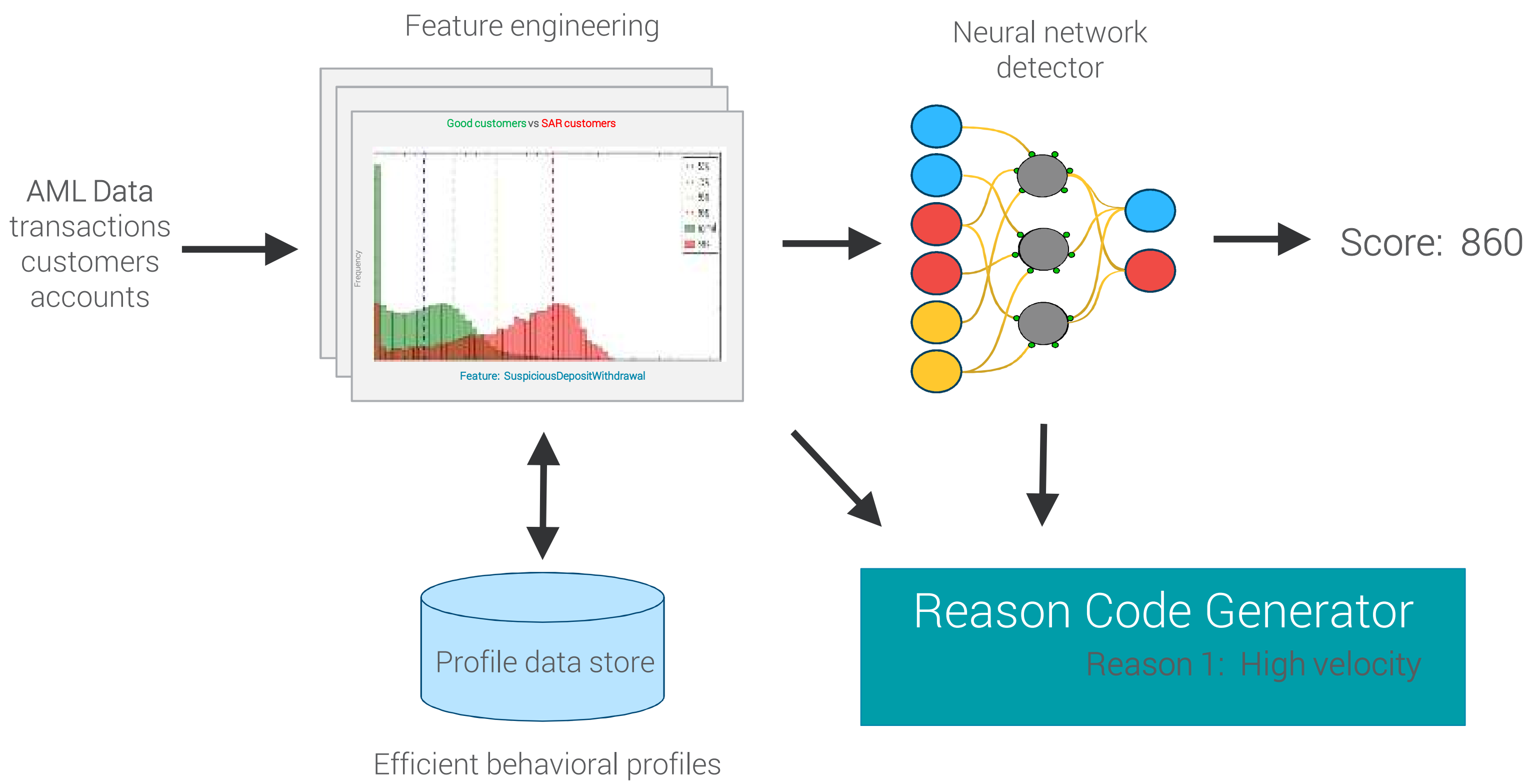
- Find bad actors based on misalignment with clusters
- Find suspicious activity that was previously undetected.
- Historical SAR data NOT required to train model

Patent: US 15/074,856 (2016)
Patent: US 15/074,977 (2016)

AML Advanced Analytics - Technology

Advanced Machine Learning Algorithms and XAI

AML Threat Score

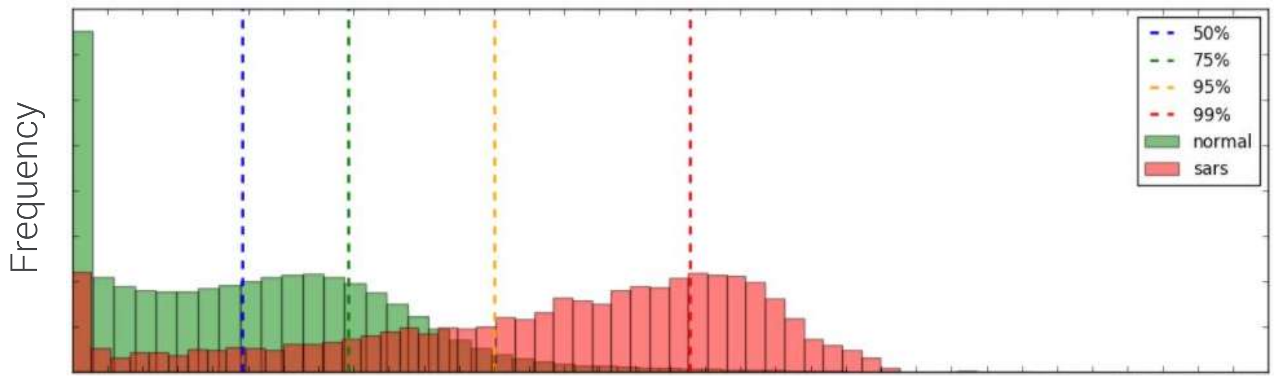


Patent: US 15/074,856 (2016)
Patent: US 15/074,977 (2016)

Example AML Analytics feature: Rapid deposit/withdrawal activity

- Feature separates good and SAR customers
  - Gives a ranking, rather than black-and-white rule decision
- Features are easily explained to regulators
- One of many features input to machine learning
  - Weight in score determined by algorithm

Good customers vs SAR customers



SuspiciousDepositWithdrawal - Feature histogram

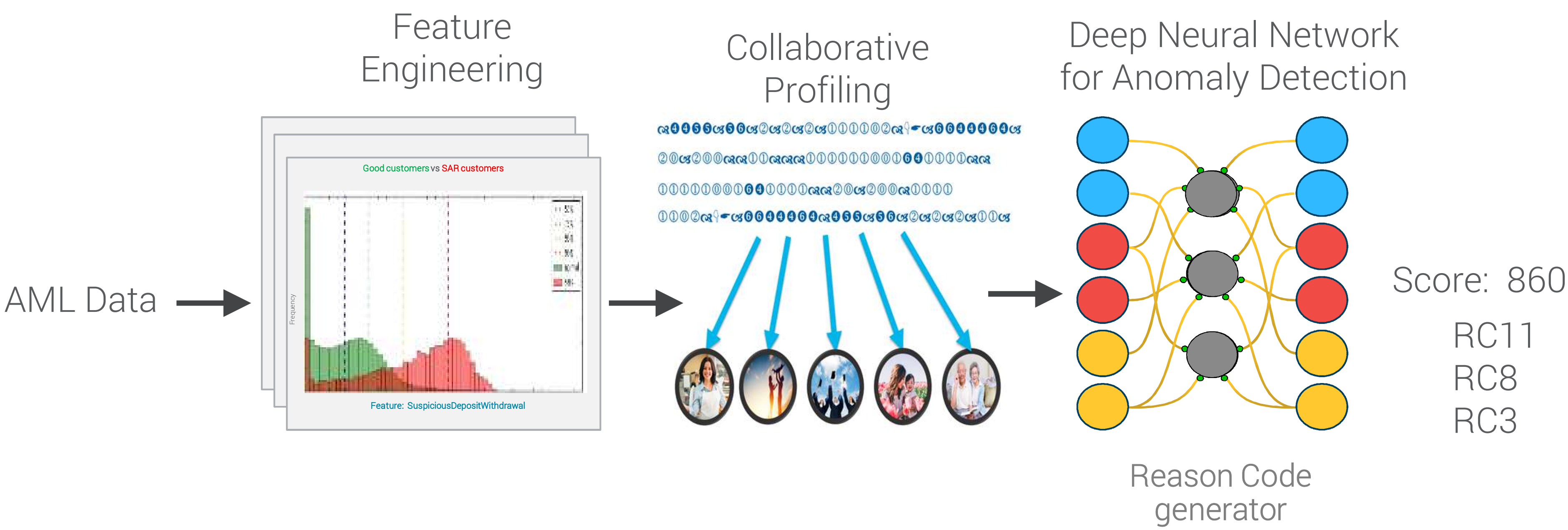
Patent: US 15/074,856 (2016)
Patent: US 15/074,977 (2016)

Feature groups cover important AML typologies

- Feature groups track behavior including:

- Structuring/smurfing
- Suspicious wire transfers
- Risky international activity
- Cash and check activity
- Money collective accounts
- Dormant account and young account activity

AML Soft-Clustering Misalignment Score



Vocabularies to describe transaction behavior

Think of transaction behavior and events as words from a vocabulary

Current Account

Amounts
Wire Transfer Country
Access Channel

Example word:

"$500-$750_Wire_FRA"

Word	
"$500-$750_Wire_FRA"	☙
"$100-250_EFT"	🙢
"$250-$500_EFT"	☟
"$500-$750_Wire_ITA"	❻

➡ ☙❹❹☛🙢🙢❺❺☙❺❻☙②☙②☙②☙①⊙①⓪②☙☟☚☙❻❹❹❻❹☙

The stream of behavior is seen as the sequence of words

Patents 14/796,547 (USA) ,14/613,300 (USA)

Learning archetypes from transactions: Collaborative Profiling

Customer's data stream:

☙❹❹❺❺❧❺❻❧②❧②❧②❧①①①①⓪②☙☝☚❧❻❻❹❹❹❻❹❧

②⓪❧②⓪⓪☙☙①①☙☙☙①①①①①①⓪⓪①❻❹①①①①☙☙

From many other customers

①①①①①⓪⓪①❻❹①①①①☙☙②⓪❧②⓪⓪☙①①①①

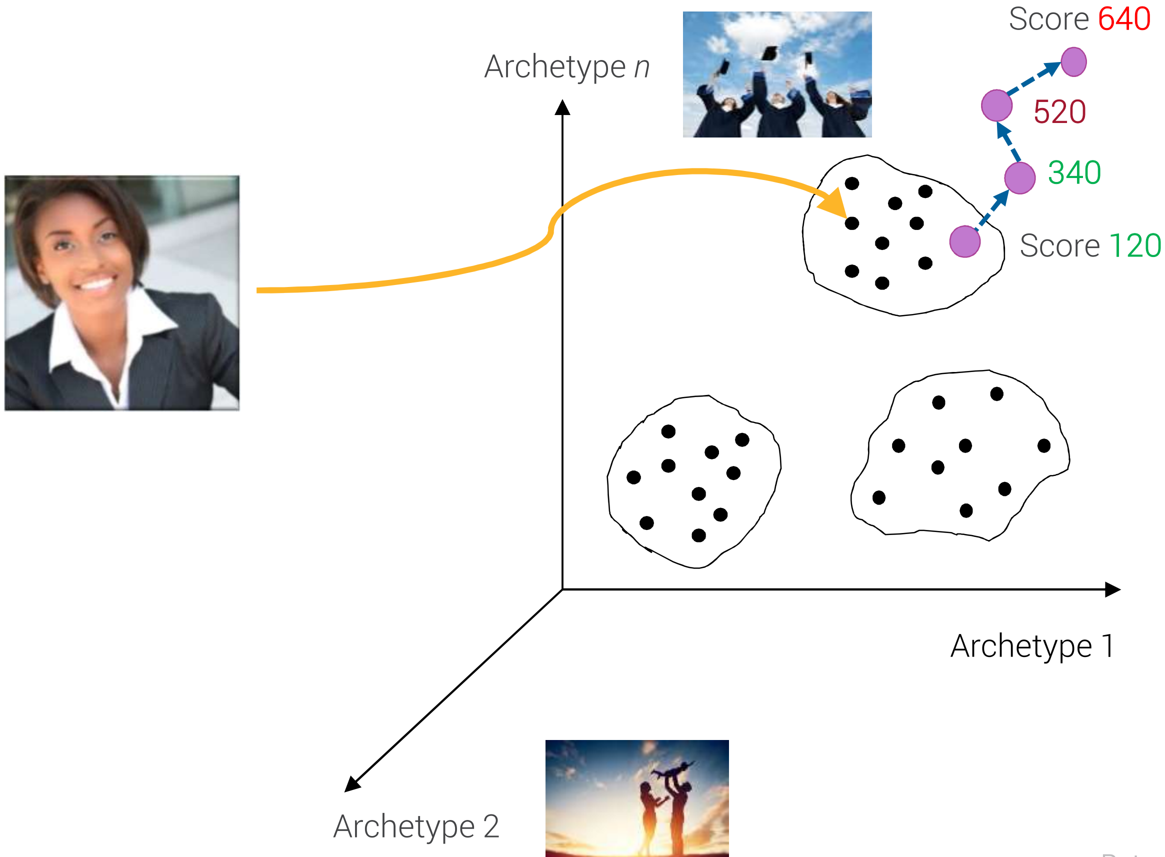
①①⓪②☙☝☚❧❻❻❹❹❹❻❹☙❹❺❺❧❺❻❧②❧②❧②❧①①❧

- Bayesian Learning
  - Unsupervised
  - Learn archetypes from millions of customers.

Learned Archetypes (~10's)

Patents 14/796,547 (USA) ,14/613,300 (USA)

Clustering archetypes: Misalignment with clusters is suspicious



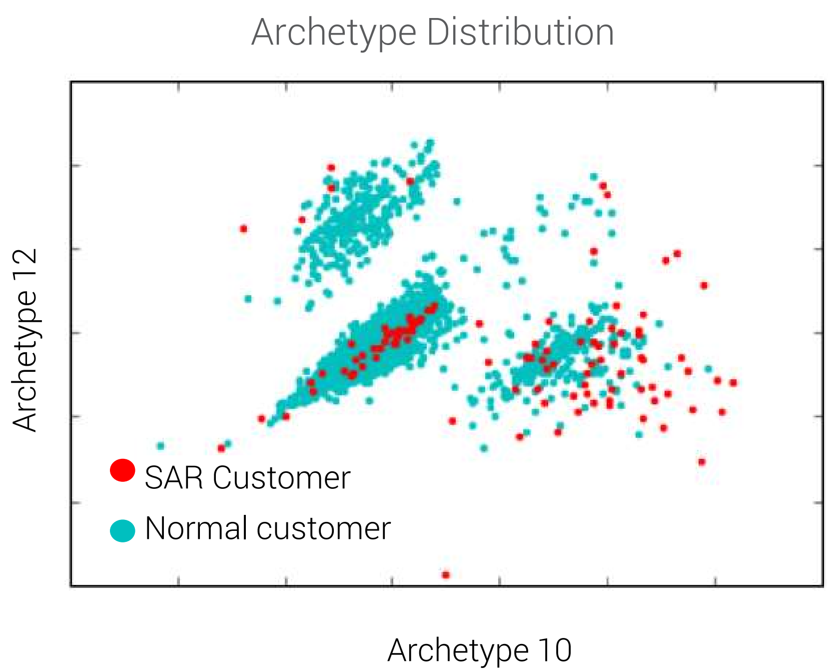
Scenario: Existing customer moves out of cluster:

- Sleeper account being activated

Patents 15/074,856 (USA) ,14/074,977 (USA)

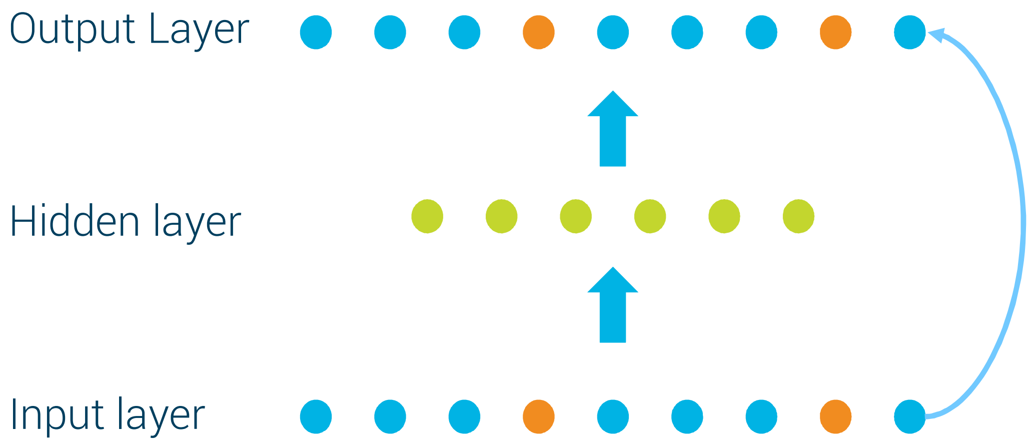
Real-World AML Example: SAR distribution in archetype space

- Many SARs are outliers from normal customers along certain archetypes



Autoencoders for unsupervised anomaly scoring

- Autoencoders are deep neural nets trained to represent/compress input by minimizing reconstruction error.

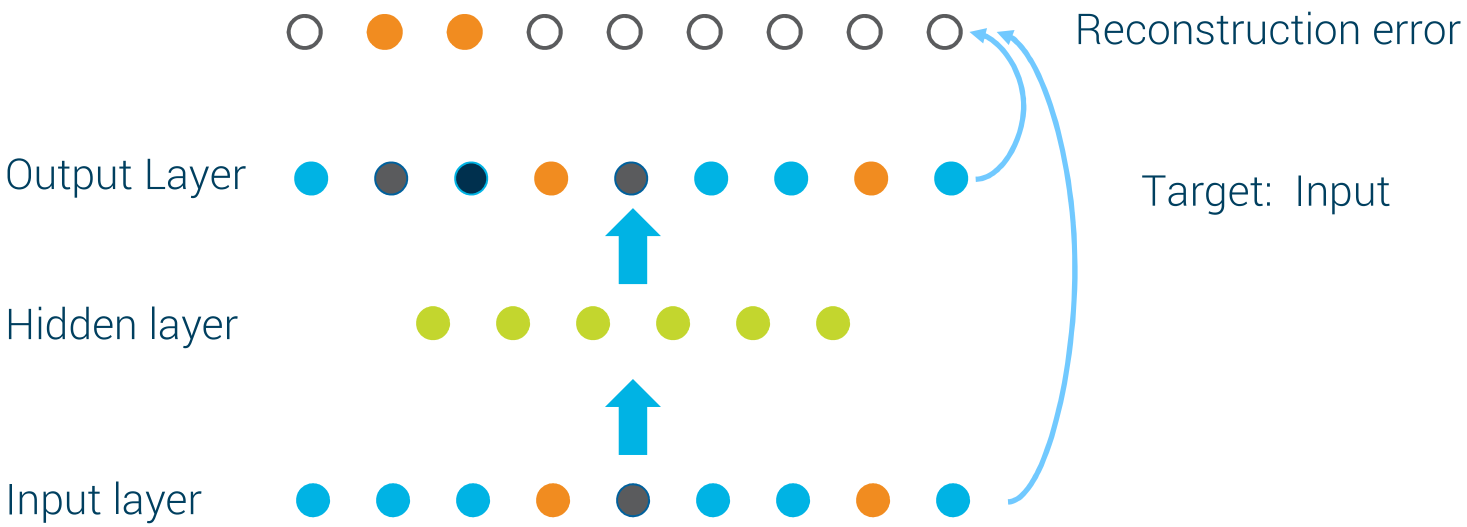


Target: Input

Train to minimize difference between input and output through “bottleneck layers”

Autoencoders: Reconstruction error measures similarity to training data

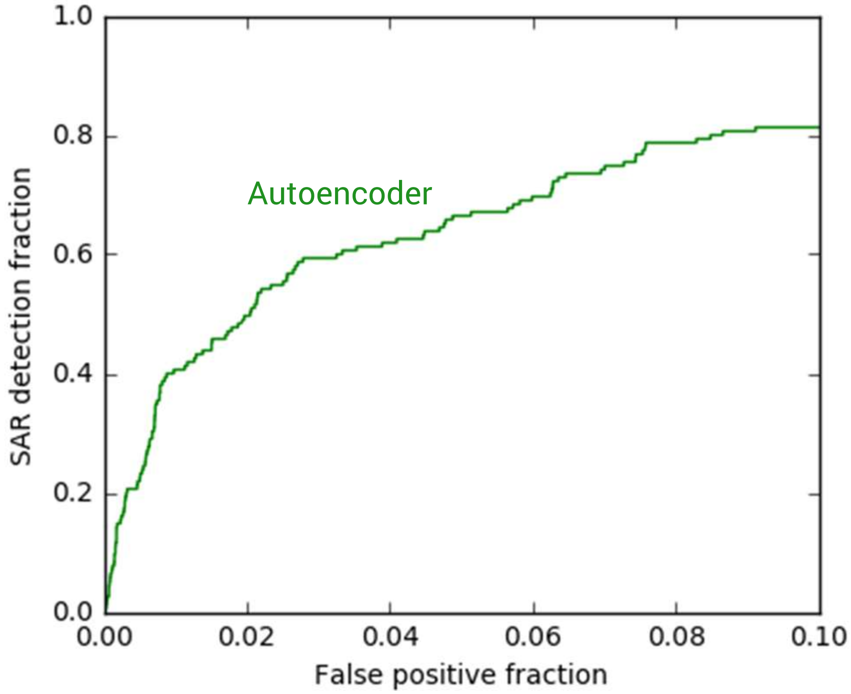
- For anomaly scoring, this reconstruction error indicates how much a sample differs from the training population.



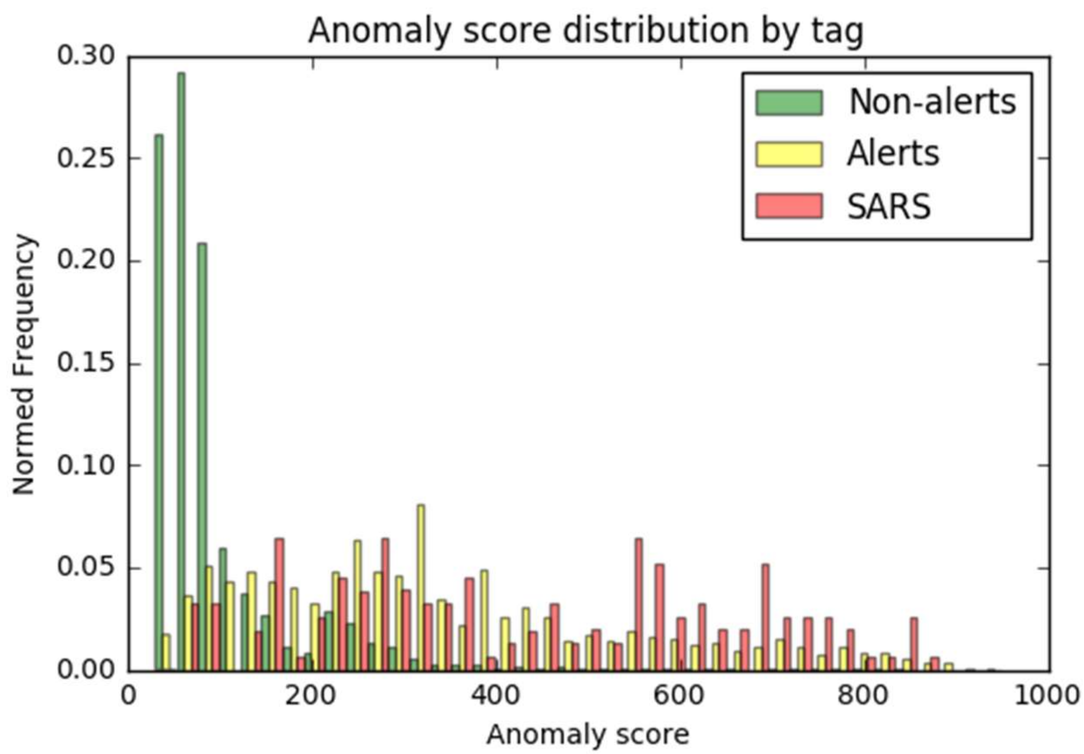
Patent PCT/US15/63395

Real-world AML application: Autoencoder finds outlier in archetype space

- Autoencoder trained on Collaborative Profiling archetypes
- High scores when autoencoder finds archetype mixtures very different from training set.

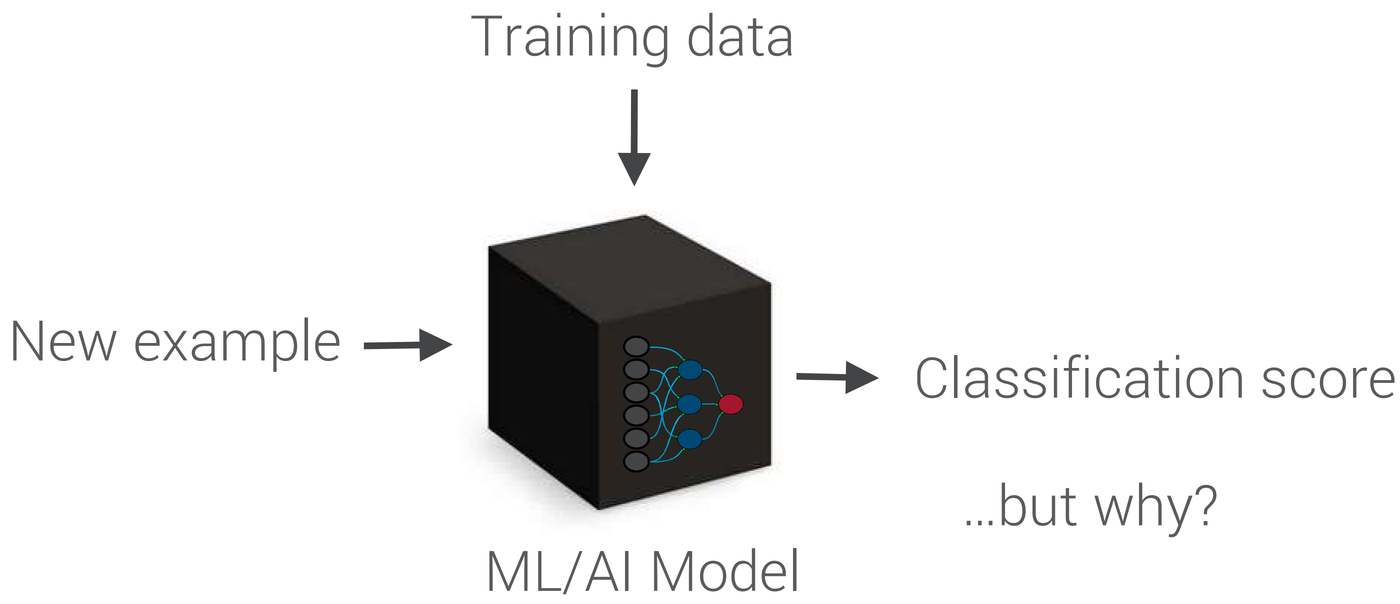


AML Advanced Analytics: Performance Metrics



Challenge: Explaining how a machine learning model gives a score

- Machine learning models (like neural networks) are typically a black box.



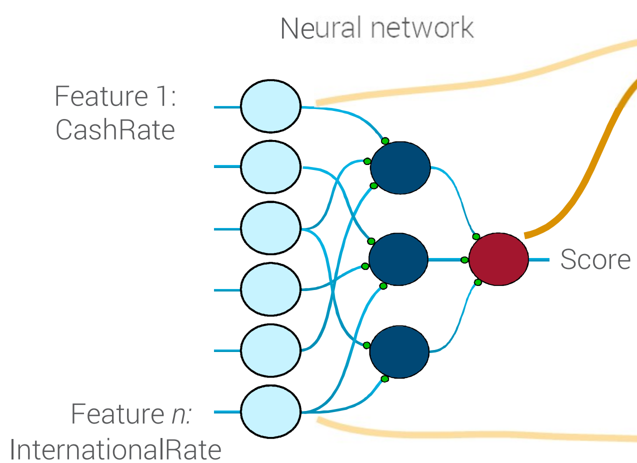
AML Advanced Analytics – Explaining the scores

- AML Advanced Analytics produces *Reason Codes* and *Quantitative Explanations* to answer:
  - *Why did a certain customer score high (or low)?*
  - *What types of transactions should be further investigated? For what scenarios?*

- FICO reason code and explanation technology based on rich IP:
  - Reason Reporter: Patent US 5,819,226 (1998)
  - Quantitative explanations, real-time tracking: Patents: US 8,027,439, 8,041,597 (2008)

Reason reporter technology – Design time

Explaining neural network decisions



Feature 1

Bin num.	Bin min.	Num. obs.	Expected Score	Reason Code
1	4.0-5.5	4353	850	21
2	2.5-4.0	5323	650	21
3	0.5-2.4	8342	400	21

⋮

Feature 2

⋮

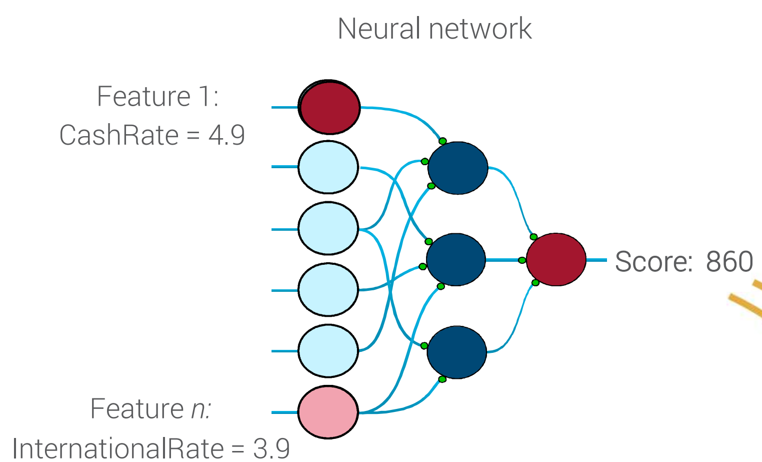
Feature *n*

Bin num.	Bin min.	Num. obs.	Expected Score	Reason Code
1	6.5-8.0	1285	920	11
2	3.8-6.5	8951	730	11
3	2.2-3.8	10115	350	11

- Run data through trained model.
- Find feature binning and expected scores.

Patent US 5,819,226 (1998)

Reason reporter technology – Run time



Feature 1

Bin num.	Bin min.	Num. obs.	Expected Score	Reason Code
1	4.0-5.5	4353	850	21
2	2.5-4.0	5323	65	
3	0.5-2.4	8342	40	

Highest ranked reason across all features

Feature 2

⋮

Feature *n*

Bin num.	Bin min.	Num. obs.	Expected Score	Reason Code
1	6.5-8.0	1285	920	11
2	3.8-6.5	8951	730	11
3	2.2-3.8	10115	350	11

- Score customer with neural network
- Rank features based on learned binning
- Select highest ranking reason codes

Patent US 5,819,226 (1998)

Governance

- Two components of governance
  - Internal and regulatory approval of model
  - Each customer-level transactional score produces a reason code to make each decision explainable

- FICO delivers a "Model Governance Document" with each model
  - Describes model features and FICO process
  - FICO will work to customize the content of doc to meet regional needs of regulators

- FICO AML Advanced Analytics model source code is proprietary IP
  - Not available for external review

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AML Advanced Analytics - Pilot Projects

Proof-of-Value Project

Phase 1: Proof-of-Value Process – Data Preparation (1 of 2)

Data Mapping
1-2 Weeks

Jointly work to map client data with model data needs.

@client-site

Data ETL
2-3 Weeks

Transform data into the FICO Data format.

@off-site

Data Validation
1-2 Weeks

Ensure data-quality does not impact model.

@off-site

FICO

- Scientists, PS, model data-needs & field-definitions
- Analytics team will transform data and identify any issues
- Data-quality reports with mapping & mismatch information

CIBC

- Data dictionary and samples

  Personnel: Key stakeholders, IT data experts, AML experts
- 12 months data flat-file: transactions, customer, account, SARs & alerts

  Personnel: IT data experts, AML experts
- Clarification, review, and potential data fixes

  Personnel: IT data experts, AML experts

Phase 1: Proof-of-Value Process – Model Building (2 of 2)

Model Evaluation

3-4 Weeks

Evaluate consortium Analytic Models on client historical data.

@off-site

Model Tuning

3-4 Weeks

Tune and calibrate Models (parameters, weights, etc.).

@off-site

Model Report

1 Week

Review results, new-insights and determine next-steps

@client-site

FICO

Progress-updates, data-issues, and clarification-requests

Progress-updates, data-issues, and clarification-requests

Report comparing Advanced Analytics to incumbent system

CIBC

Domain-experience, expert-advice

Personnel: AML experts, Data science

Feedback on alerts and case-priorities generated by model

Personnel: AML experts, Data science

Feedback and next-steps

Personnel: All stakeholders

FICO Decisions

Thank You

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