OLIVER WYMAN

OVERVIEW OF ADVANCED ANALYTICS AND DATA IN RISK APPLICATIONS: TRENDS, ENABLERS AND APPLICATIONS

MARCH 20, 2018

DIGITAL

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1 Introduction

Technology and data are currently driving change in risk management across the banking sector

Technology-related enablers for change in risk management

I. MACHINE LEARNING

A. Data science and advanced analytics (i.e. machine learning) provide new and sharper insights
B. Enables optimization of decision-making at key business applications

II. ARTIFICIAL INTELLIGENCE

A. Capabilities in software to make decisions and actions without explicit instructions
B. Can leverage natural language processing
C. Enables a number of new commercial applications

III. NON-TRADITIONAL DATA

A. A number of non-traditional data sources is becoming available for financial services players
B. Enables generation of new insights across the credit value chain

IV. ADVANCED PROCESS AUTOMATION / DIGITIZATION

A. Automation of repeatable tasks through process digitation is ongoing
B. Combined with other enablers, enables considerable efficiency and effectiveness improvements for Risk

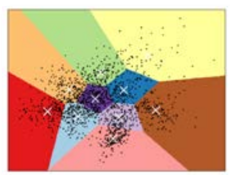
1. Machine Learning

The term Machine Learning is often used to refer to a set of advanced algorithms that go beyond the traditional regression methods

Machine Learning
E.g. Random Forest, Neural Network, K-means…

Unsupervised Learning Problem – *"X"*
Training with unlabeled data

Clustering
Algorithms group objects into clusters

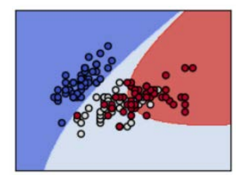


Association
People that buy X also tend to buy Y

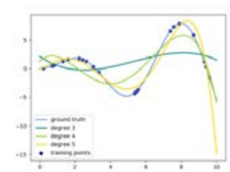
{onions, potatoes}
➔ {burger}

Supervised Learning Problem – *"Y = f(X)"*
Training with known output

Classification
Output variable is the class of the object



Regression
Output variable is a real value



2. Artificial Intelligence
Different software capabilities are being combined and refined to create what we know today as AI

Artificial Intelligence: Capabilities in software that can make decisions and take actions without explicit instruction for each scenario(s) including an ability to learn and improve on results over time

Language	Decision Making	Perception	Logic
• Speech Recognition • Natural Language Processing & Generation • Translation	• Fuzzy Logic • Pattern Recognition • Genetic Algorithms	• Image Recognition • Object Recognition • Sentiment analysis	• If, Else comparisons • Sort • Match • Search • Ranking

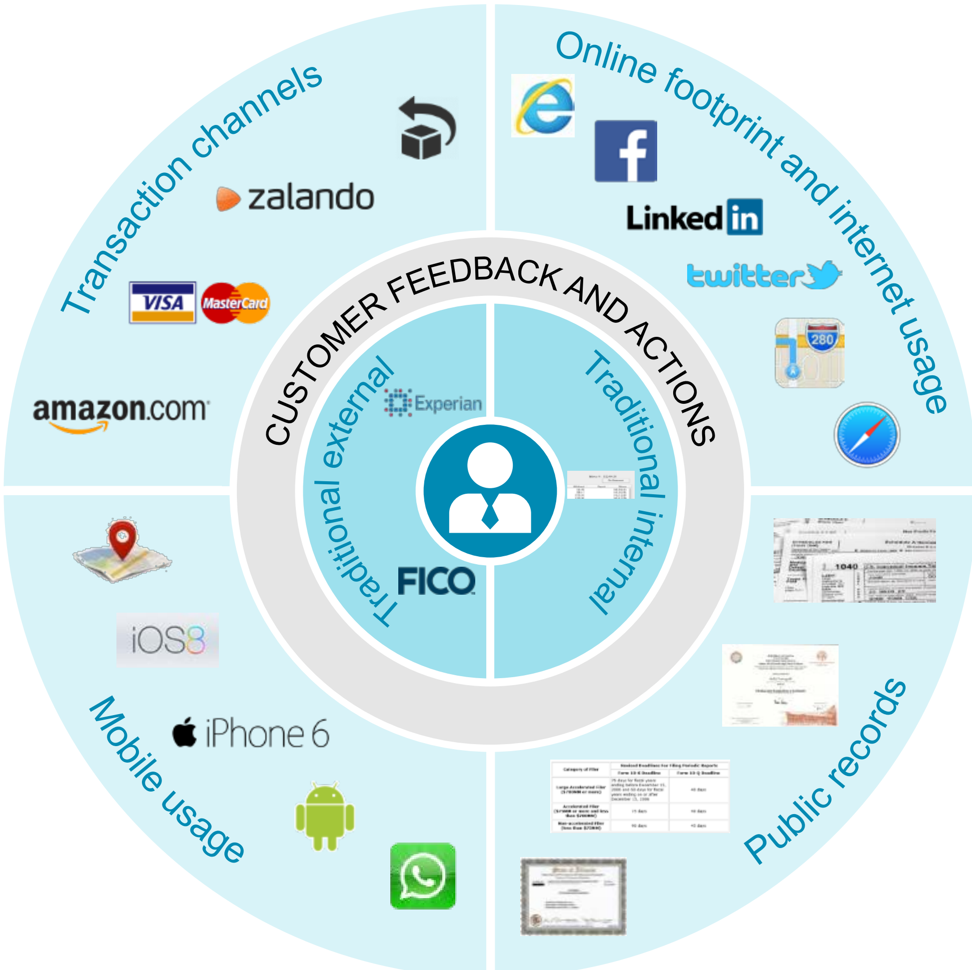
These capabilities are combined and refined to create what we know as AI today:

- **Personal assistants**: Apple Siri, Amazon Alexa, Google Assistant
- **Self-driving cars**: Google Waymo, Uber ATC, GM Cruise Automation
- **Purchase predictions and recommendation**: Amazon Recommendations, Netflix, Spotify, Pandora
- **Financial analysis**: American Express Fraud Detection, Wealthfront Investments, JP Morgan COIN
- **Online customer support chatbots**: KLM Messenger, TDAmeritrade Ted, H&M Kik
- **Smart home devices**: Nest Thermostat, June Intelligent Oven

3. Non-Traditional Data

Lenders are using a broad range of traditional and non-traditional data sources to improve the predictive power of models

Digital data sources: Retail



Non-traditional data sources: Corporate

1. **Web scraping:** Automatic scraping of news articles in web relating a corporate client (e.g. top 20 news)
2. **Semantic news analysis:** Semantic analysis of news to identify negative signals as they occur, providing timely triggers
3. **Semantic annual report analysis:** Automatic analysis of Annual Reports combined with semantic analysis to infer credit signals
4. **Social media sentiment scores:** Social media sentiment scores (neutral / positive / negative) aggregated across different platforms (Twitter, LinkedIn, etc.)

4. Advanced process automation
Robotic process automation (RPA) is reducing manual effort in Risk processes

Robotic process automation (RPA) delivers “software robots” that replicates routine and standard tasks performed by humans, without disrupting existing processes, with very short implementation time (in weeks) and with quick ROI (less than 3 months for simple processes)

RPA potential identification

- Reporting
- Monitoring & testing
- Credit proposal
- Data management
- Validation

Business changes / Stability of systems environment	In flux	Stable
Low	Benefits of automation offset by rework	**Optimal case for RPA**
High	Benefits of automation offset by cost of change	Benefits of automation offset by cost of change

Stability of systems environment

RPA implementation process

- **A** Analyze current process map
- **B** Adjust to allow efficient RPA implementation
- **C** Train software robots to perform the process
- **D** Adjust and optimize over time

Case study – stress-testing process industrialization

- European based Tier 1 Bank
- **Project objectives**
  - Develop a web-app to automate and manage report production
  - Quantify the current costs of the process and impacts of the tool
- **Impact achieved**
  - Tool successfully deployed in production environment
  - Replaced and automated work of ~5 large Excel models completely
  - Estimated 40% reduction in process resourcing spend as a result of the tool

Source: Institute for robotic process automation – http://www.irpanetwork.com/, Oliver Wyman & Celent analysis

2 | Example applications

Oliver Wyman has seen advanced risk applications through the credit process – *deep dives to selected examples follow*

High-level credit process

Overall Bank Strategy

- **Customer Acquisition**
- **Initial decisioning** (auto approve/reject or manual underwriting)
- **Post approval processing**
- **Recovery & Provisions**

Advanced Analytics Applications

- Propensity
- Pricing models
- Affordability Models
- Limit management
- Customer value calculation
- Debt restructuring tools
- Credit models
- Customer segmentation
- Fraud detection
- Stress testing
- Credit portfolio tools
- Early warning system

Examples

Digital Lending

1. **Retail:** Underwriting using advanced modelling
2. **SME:** Digital cashflow-based lending
3. **Mid-market:** Automating decision-making

4 AML/KYC automation

- Advanced analytics
- Reduce false positives

Affluent client targeting

- Social Media data analysis

Price elasticity

- Machine Learning for precise estimation of customer price elasticity

Compliance chatbot

- Automatic handling of basic compliance requests / questions

5 Collections call-centre optimization

- Machine Learning to create caller strategy (who to call, when to call, etc.)

Social media sentiment analysis

- Company sentiment scoring

Web scraping for trigger events

- News alerts from trigger events

Case study #1: Machine Learning Enhanced Retail Lending

Oliver Wyman used machine learning algorithms to optimize retail credit decisioning while complying with regulatory requirements

AMBITION

- Client was subsidiary of a large international bank with **aim to grow** consumer lending
- Key levers for growth
  - Increased approval rates
  - Increased level of automation
  - Constraint: Risk costs
- Additional aspirations
  - New channels
  - New partnerships

PROBLEMS

- **Shortcomings** in decision-making set-up
  - Too many scorecards
  - Low predictive power
  - Scorecards optimized by channel, hard to open new channels
- **Low approval rates**
  - Many rejections due to policy rules
  - Unable to increase approval rates without significantly increasing risk costs
- Considerable **manual effort**

OW APPROACH

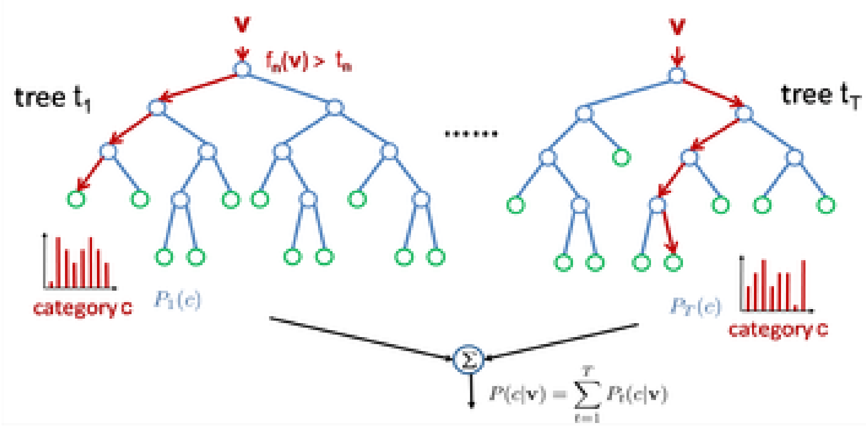
- **Rebuild scorecards** using traditional techniques – in order to be compliant to regulatory requirements
- Revise scorecard outputs using **machine learning** – optimize final decisions using information left out of scorecards
- Redesign the **decision making process** to reflect the changes

Illustrative

Case study #1: Machine Learning Enhanced Retail Lending

Random forest algorithm was used to intelligently combine scorecard results and soft policy rules for higher predictive power

Random Forests improve bucketing by creating multiple decision trees which "vote" on how to bucket customers

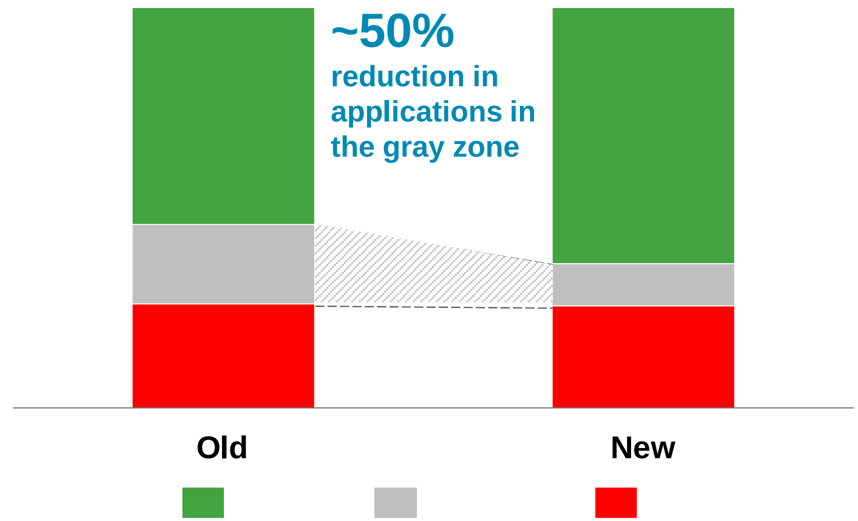


- **Random Forest** calculates PDs of customers by combining output of 1000+ decision trees
- Scores of customers that are found by most decision trees "not likely to default" are **adjusted downwards**

Technical note: *Random Forest is an automated equivalent of an "expert panel", each expert/tree using their own criteria to establish whether a customer is likely to default*

Source: Oliver Wyman analysis

Breakdown of decisions with old and new approach
Based on exposure values



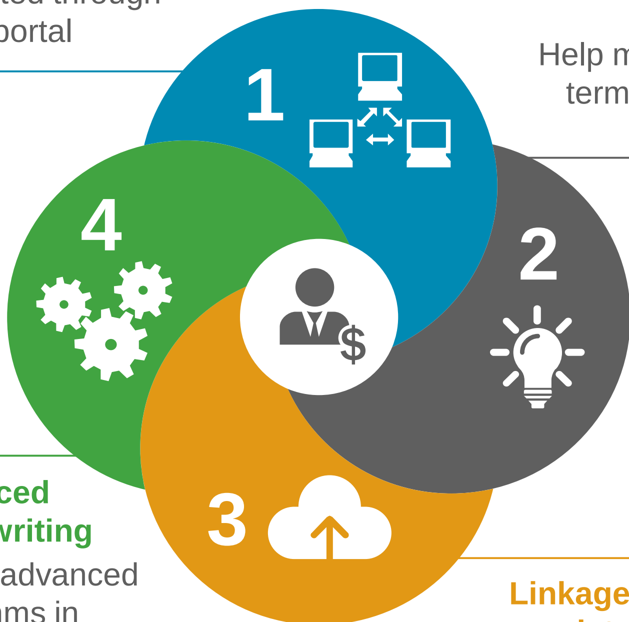
- New model was **better in classifying** customers correctly to "Approve" and "Reject" categories
- **Gray zone** represents borderline customers that need to be manually evaluated
- Introduction of new factors and advanced modelling techniques helped **minimize customers in gray zone**

Case study #2: Automation of SME lending with Machine Learning
Real time underwriting is adopted in SME lending space for a major Australian bank

Oliver Wyman helped developed the end to end digital platform including the enabling analytics..

Digital application platform
Facilitated through online portal

Defined new innovative product
Help meet short term cashflow needs



Advanced underwriting
Use of advanced algorithms in defining the score-card and overall strategy

Linkage to cloud data sources
Seamless integration of user data

..and helped client achieve the business objectives

1 **REAL TIME** online decision making based on largely automated policy rules and decision engine

2 **1–3 DAY** fulfilment

3 Enabled **lower acquisition cost** compared to traditional channels

Case study #2: Automation of SME lending with Machine Learning
Transaction level data from multiple sources enabled real time decision making

Sources of transaction level data and their availability

	***Existing to Bank** – Primary Account and/or Borrowers*	***Existing to Bank** – Others*	**New to bank**
Internal – Bank account statement	✓✓		
Internal – Merchant payments	✓✓	✓✓	✓
External – "Off us" account statements	+	✓✓	✓✓
External – Accounting packages	✓✓	✓✓	✓✓
External – Online market places	✓✓	✓✓	✓✓

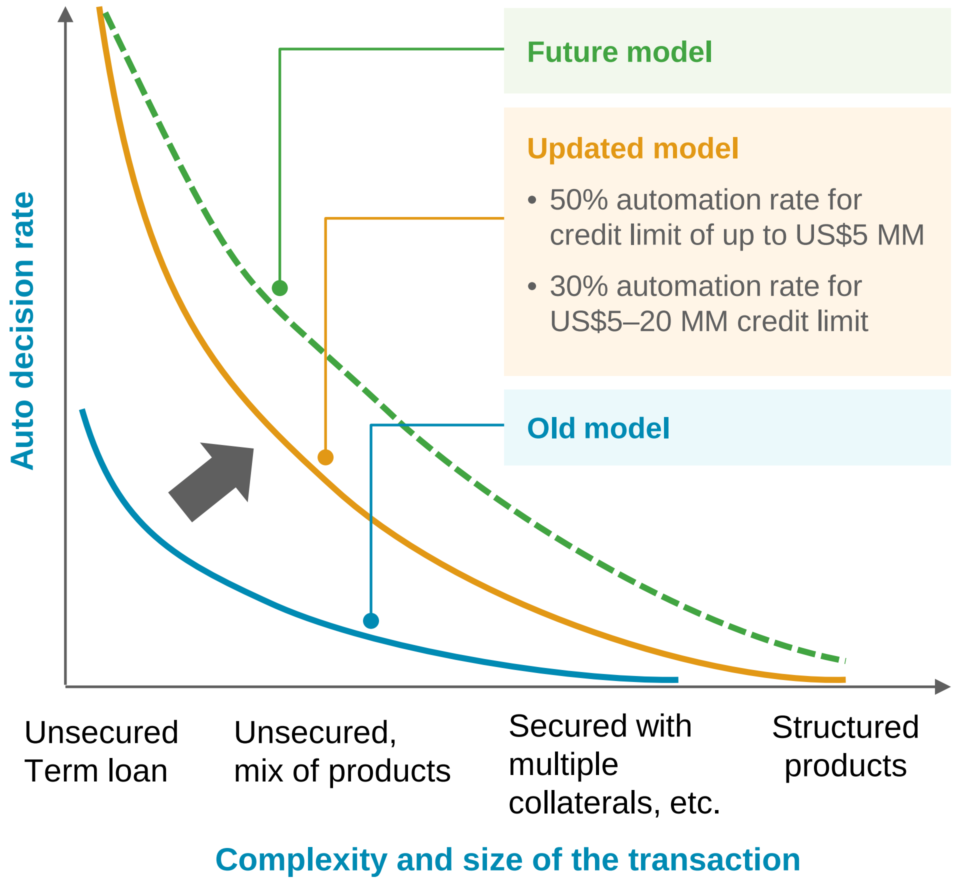
Legend ✓✓ *Data useful and sufficient* ✓ *Data useful but **may not be sufficient*** + *Additional data – **Good to have*** *Cash inflow only*

Digital links built to data sources to enable real time decision making

Illustrative

Case study #3: Digital Lending in Mid-Market

The bank employed more sophisticated retail-like credit models for its Mid-Market / Commercial lending segment for automated credit decisioning



- Peers typically adopt automated underwriting with a tiered strategy
  – Loan exposure
  – Risk appetite, and
  – Model's predictive power

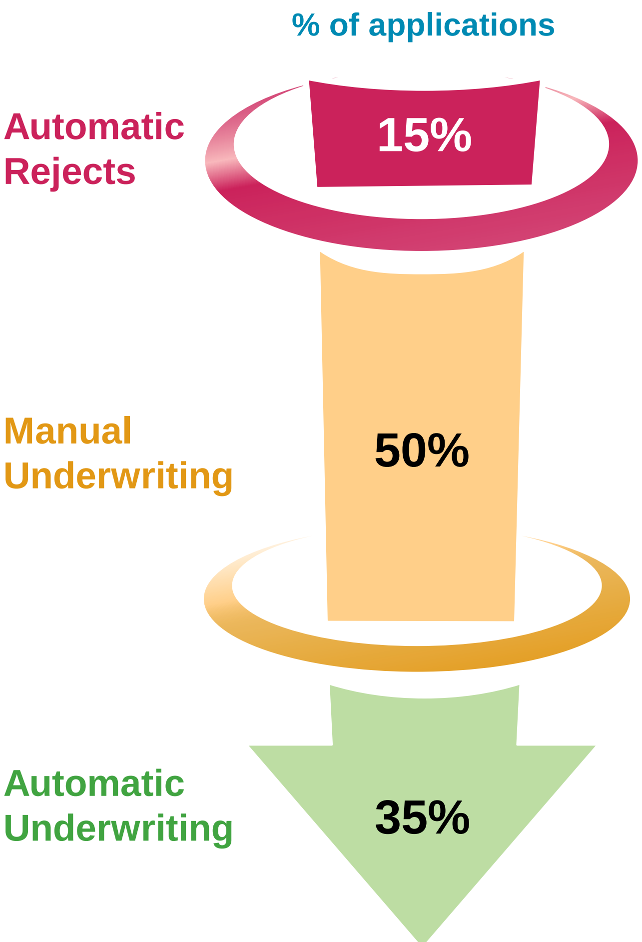
- Future automation level can be increased
  – Richer data
  – Longer data period
  – Higher risk appetite
  – Higher level of standardization for products, covenants and governance

The level of automation that can be achieved in credit decisioning depends on the complexity of the deal and size of the transaction

Case study #3: Digital Lending in Mid-Market

The referral model automated 50% of credit decisions, allowing underwriters to focus manual efforts on higher risk files

Referral model automation rate



Rules

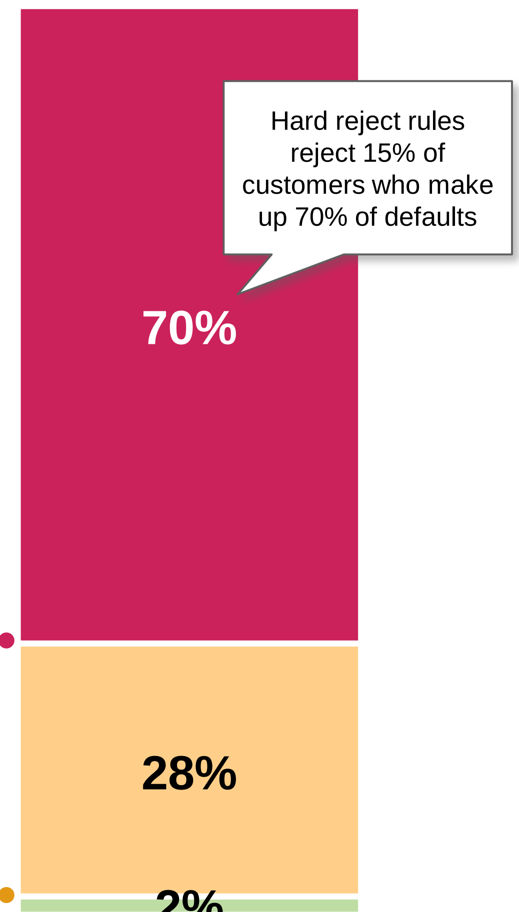
Hard reject rules

- PD cut-off (≥ X%)
- NPL record
- Restructuring flag
- …

Transfer to manual rules

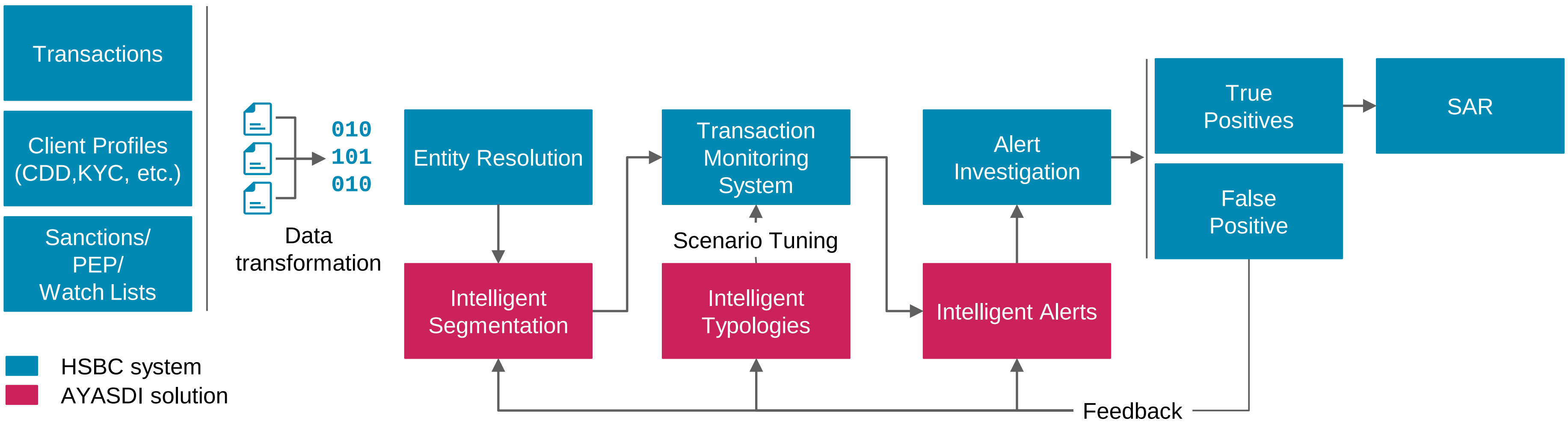
- Delinquency record on credit bureau
- Early warning signals
- PD cut-off (≥ Y%)
- Limit size (≥ Z MM TL)
- Expected loss cut-off (≥ W TL)
- …

Share of all defaults



Case study #4: Machine Learning for AML Transaction Monitoring

HSBC implemented AYASDI’s cognitive Robotic Process Automation (RPA) solution to automate transactions screenings as part of AML investigations



Intelligent Segmentation

Segment customers and transactions for **more optimized scenario threshold tuning**

- Optimal categorization of high-dimensional customer and transaction data into segments with similar characteristics
- Advanced analysis based on Topological Data Analysis (TDA) techniques

Intelligent Typologies

Identify anomalous behavior in customers to **uncover new typologies** not covered by existing scenarios

- Detects anomalies and tells which ones are least likely to occur (ranking)
- Learns over time based on feedback

Intelligent Alerts

Accelerate processing and clearing of alerts backlog by **automatically prioritizing alerts**

- Groups alerts and ranks them based on probability of resulting into a suspicious filing (e.g. L3, L2, L1)

Source: https://www.ayasdi.com/blog/financial-services/anti-moneylaunderinghsbc/

Case study #4: Machine Learning for AML Transaction Monitoring

Augmenting AML transaction monitoring through ML can help banks stay compliant and mitigate risks in an efficient and cost-effective way

Impact of implementing Robotic Process Automation to automate transaction screenings

Reduction in false positives by 26% and improvement in true positive identification with no drop in number of cases requiring further investigation

Projected **savings of millions of USDs** based on FTE efficiencies

Identification of new and previously **missed alerts**

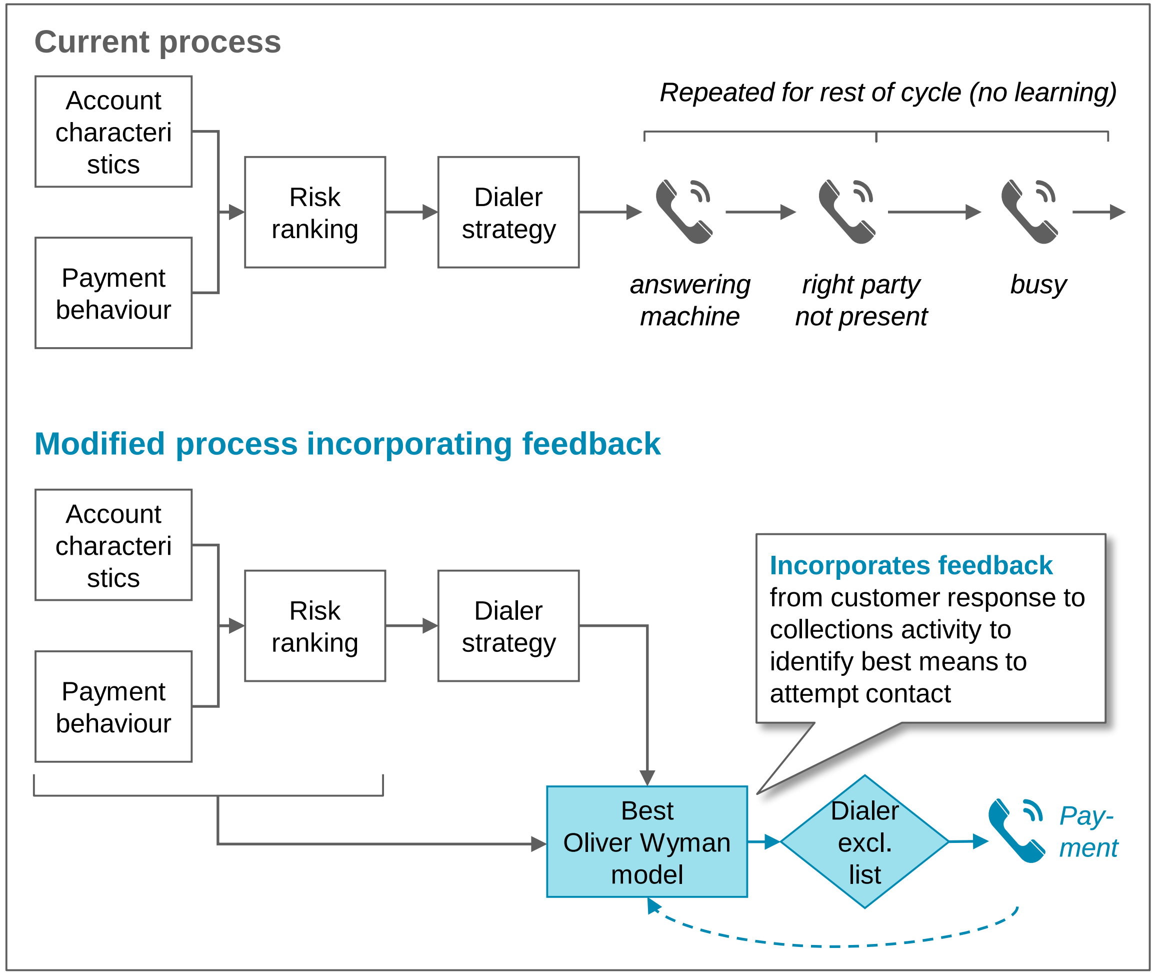
Transformation of end-to-end process for model segmentation and approval from heavily manual activity taking up to 6 months to as little as 8 hours

Source: https://www.ayasdi.com/blog/financial-services/anti-moneylaunderinghsbc/

Case study #5: Machine Learning enhanced collections process
Oliver Wyman used big data analytics to re-tool the collections process of a banking client

Our approach

- Gathered all internal data
  - Transferred 4 billion records
  - Loaded into OW secure datamart
  - Cleaned and validated data; overall, data was in great shape
- Extracted ~1000 variables
  - Extracted previously unused info
  - Created new features using hypothesis-driven approach
- Analysed dozens of algorithms and evaluated predictive performance
- Piloted to confirm performance before full, cross-border roll out



Case study #5: Machine Learning enhanced collections process

Operational improvement was achieved using advanced algorithms on the bank's existing data

TRADITIONAL COLLECTIONS PRACTICE

100–200 million
call attempts per year

BIG DATA ANALYTICS

4 billion records drawn **& 0.5 billion** calls analyzed

- Natural language processing tools generate additional insight
- Leveraged bank data (call records, risk data, demographics)

MACHINE LEARNING MODEL

60–80%
high quality predictions with Gini

- A suite of predictive models developed for decision-making process optimization

NEW CALLING STRATEGY

- Underpinned by predictive models
- Reduced unproductive call volume by 37% via dialer exclusion lists
- Route customers to best agent match

30–40%
fewer calls

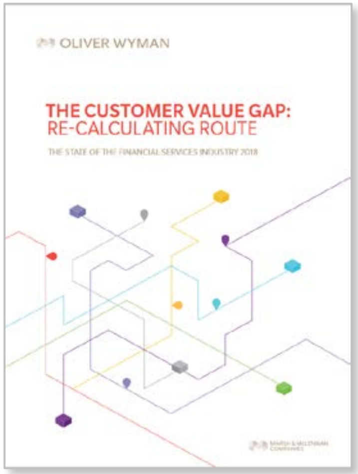
15–20%
less handling time

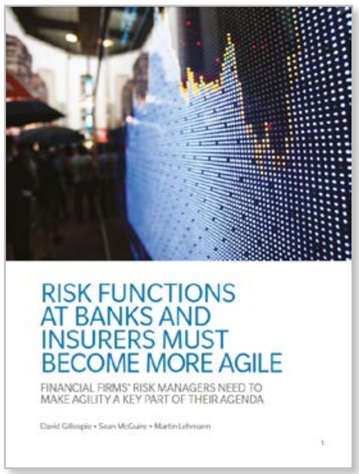
0%
change in roll rates

20–30%
expected savings in excess

Any questions?

Oliver Wyman Reports





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