



How do we operationalize
data science to fight financial crime?

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But first, let's talk

money laundering





\$2.5
Trillion



\$2.5
Trillion

\$232
Billion

< 1%

We bring productivity
to AML by
**operationalizing
data science** and
augmenting humans

Overview	Step	Published	Team	Assignee	Focal Actor	Actor ID	Total Value
Rapid Movement of Funds	Done	11/12/2019	US AML	David Butler	David Butler	7603784331	\$110K
Rapid Movement of Funds	Done	11/12/2019	US AML	David Butler	David Butler	100807709	\$36K
Rapid Movement of Funds	Done	11/12/2019	US AML	David Butler	David Butler	278360021	\$577K
Aggregate Suspicious	Done	11/11/2019	US AML	Roger Moore	Roger Moore	8003784302	\$0K
High Risk Jurisdiction	Done	11/12/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K
Referral Denial	Done	11/11/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K
Rapid Response	Done	11/12/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K
Deliberate Pattern	Done	11/11/2019	US AML	Francis Abernathy	Francis Abernathy	100807709	\$0K
Disrupt to Active	Done	11/12/2019	US AML	Francis Abernathy	Francis Abernathy	100807709	\$0K
Rapid Increase in Volume	Done	11/12/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K
Significant Cash Volume	Done	11/12/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K
Transactions Beyond Means	Done	11/12/2019	US AML	Francis Abernathy	Francis Abernathy	100807709	\$0K
Deliberate Pattern v2	Done	11/12/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K
Cash Returns	Done	11/12/2019	US AML	Roger Moore	Roger Moore	100807709	\$0K

but...
what does that even **mean**?

We use data science to find the money laundering **needle in the haystack**



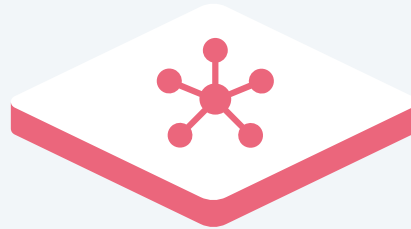
and we let humans do the **evaluation and interpretation**



Data Science in operations



**Regulatory &
FinCrime Research**



**Knowledge
Graph**



Behavioral models



Explainable models



**Continuous
Improvement**

A. Avoiding reporting requirements

Layering schemes, structuring and placement schemes, consideration of spatial and temporal dimensions, thresholds.

B. Concealing customer or beneficiary information

Identity and beneficiary obfuscation, unjustified use of intermediaries and payment processors, shell companies

C. Customer activity does not match customer profile

Comprehensive behavioral profiling, deviation from expected and peer group behavior, abnormal shift in transaction activity.

D. Exhibiting a deliberate pattern of transactions

Rapid movement of funds, regular and irregular transactional patterns, round amount and systematic patterns.

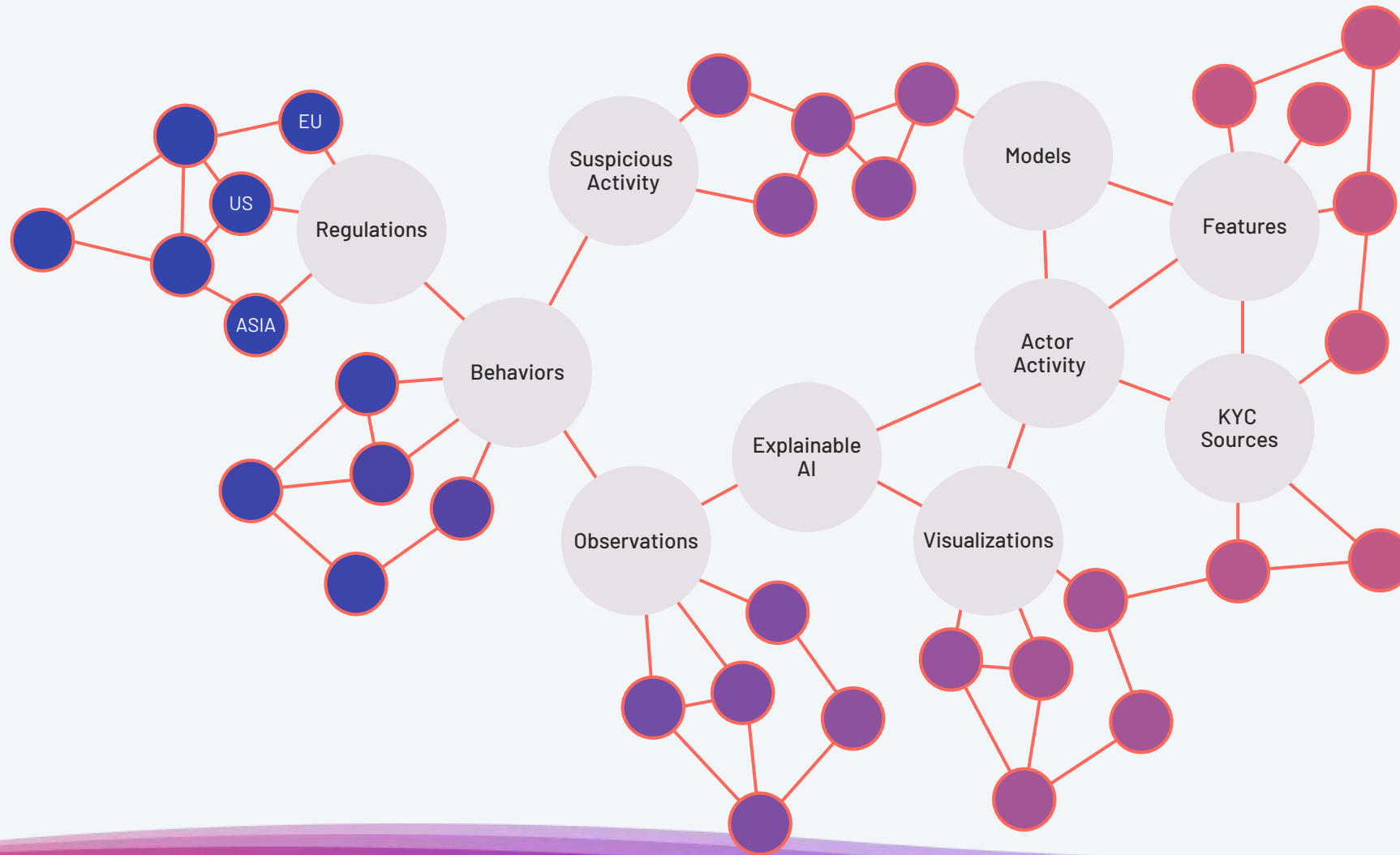
E. Unusual or suspicious customer activity

Circular fund movements, increased activity after dormancy, unusual device patterns, suspicious references.

F. Transacting in high-risk jurisdictions or sectors

Jurisdictions and sectors analyzed along multiple dimensions utilizing trusted sources to determine high risk transactions.

KNOWLEDGE GRAPH



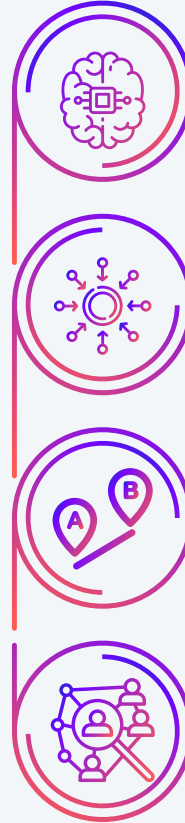
BEHAVIOURAL MODELING

relies on

building **features** that are designed to measure **suspicious activity** and make outliers and patterns **visible**

and

applying those features into a **data science** model that can score and rank actors on a given time interval.



models are trained

using an **unsupervised learning** approach in absence of labeled or enriched data

and

semi-supervised learning with feedback and labeled data

Unsupervised learning model selection

Features are used as inputs into models that score and rank each actor

Various unsupervised learning models are applicable to the set of features

There is a trade-off between predictive power and simplicity when implementing models

Scorecards

Logistic
regression

Auto Encoder

Isolation forest

Neural networks

EXPLAINABLE MODELS



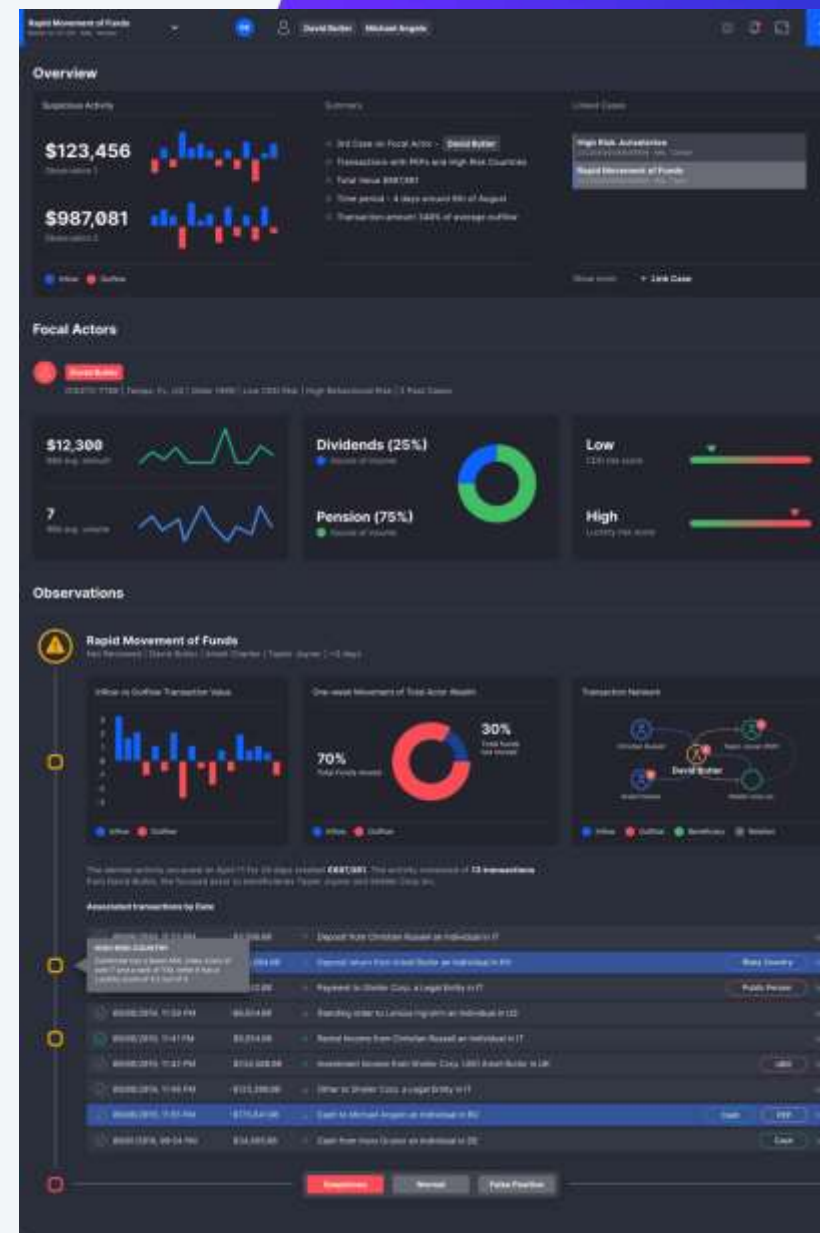
Driving engagement of analysts

- Overall effectiveness of AML program relies in no small measure on the analyst reviewing the observation



Analyst tool focusing on

- Encapsulate and present data in context of the observation
- Clear representation of contributing factors
- Easy to understand summarization
- Rich visualizations to provide insights
- Reduce case load by minimum 40%
- Reduced fatigue, better review
- 4-fold increase in coverage capability
- Automated Quality Assurance



DETECTING SUSPICIOUS BEHAVIOR USING DATA SCIENCE

Behaviors with increased money laundering risk

Certain transaction activity is known to increase the risk of money laundering.

Example:

- Transactions involving high usage of cash
- Transactions involving higher risk jurisdictions such as those with high financial secrecy, for example Cayman Islands
- Transactions with certain industry sectors that have historically been linked to increased risk of money laundering activity.
- Rapid move of funds through an account.

Other unusual behavior not explicitly defined

Transaction activity that is unusual compared to the majority is often a good indicator that something suspicious has taken place.

**Lucinity's
Knowledge
Graph**

FEATURE ENGINEERING

Feature Engineering is an essential part of our data science processes.

With the help of compliance we pinpoint the information that should be extracted from the raw data to get good indicators of certain activity.

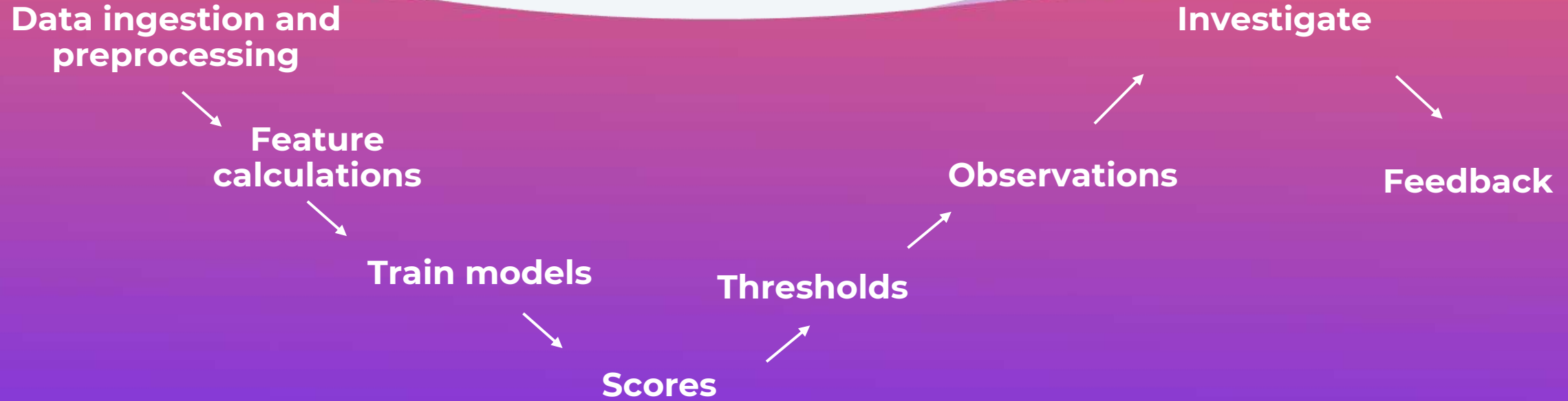
Behavior:

Customer avoiding cash reporting threshold

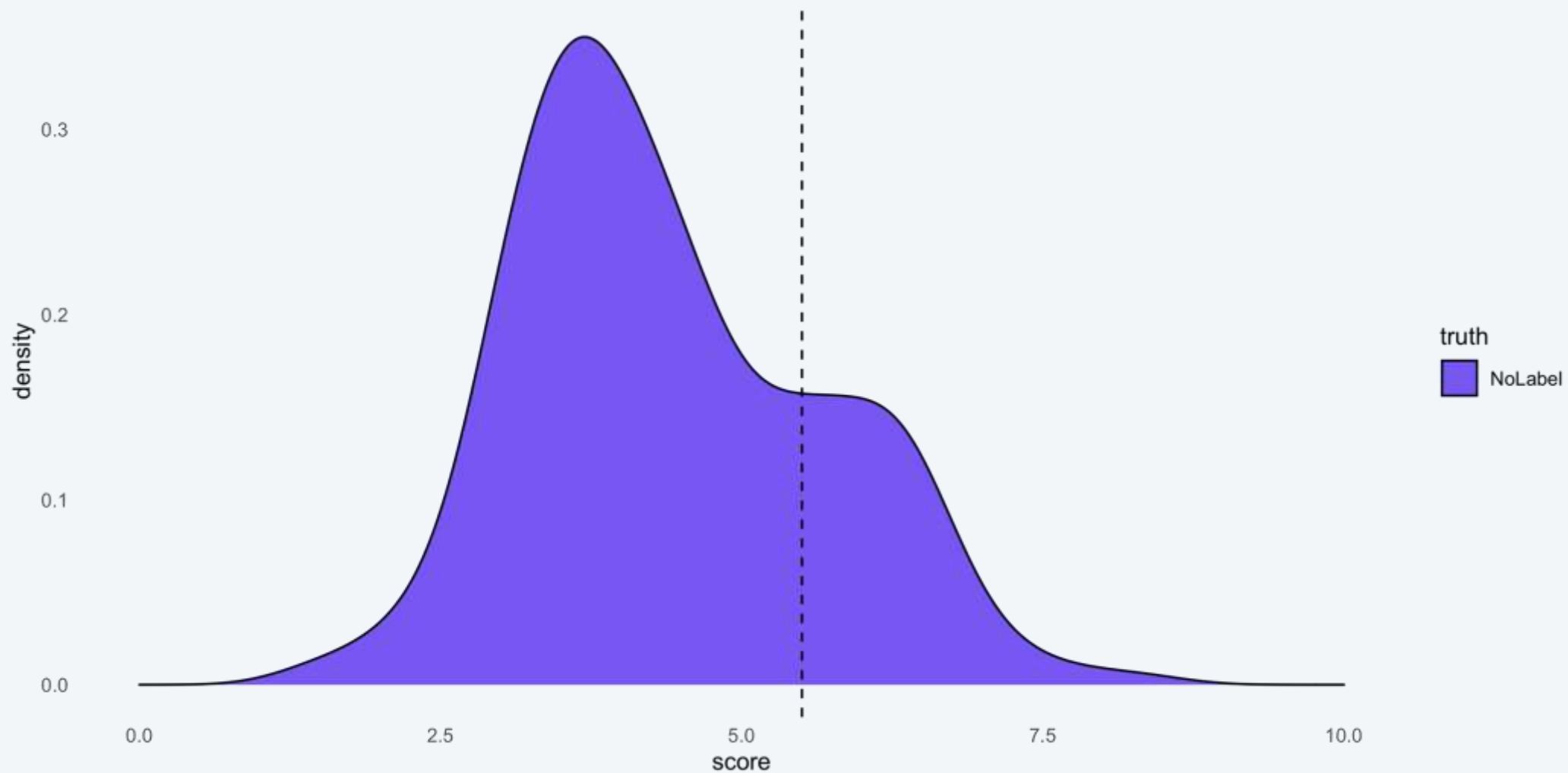
Feature examples:

- Total aggregated value of cash transactions under cash reporting threshold.
- Weighted value of cash transactions depending on closeness to cash reporting threshold.

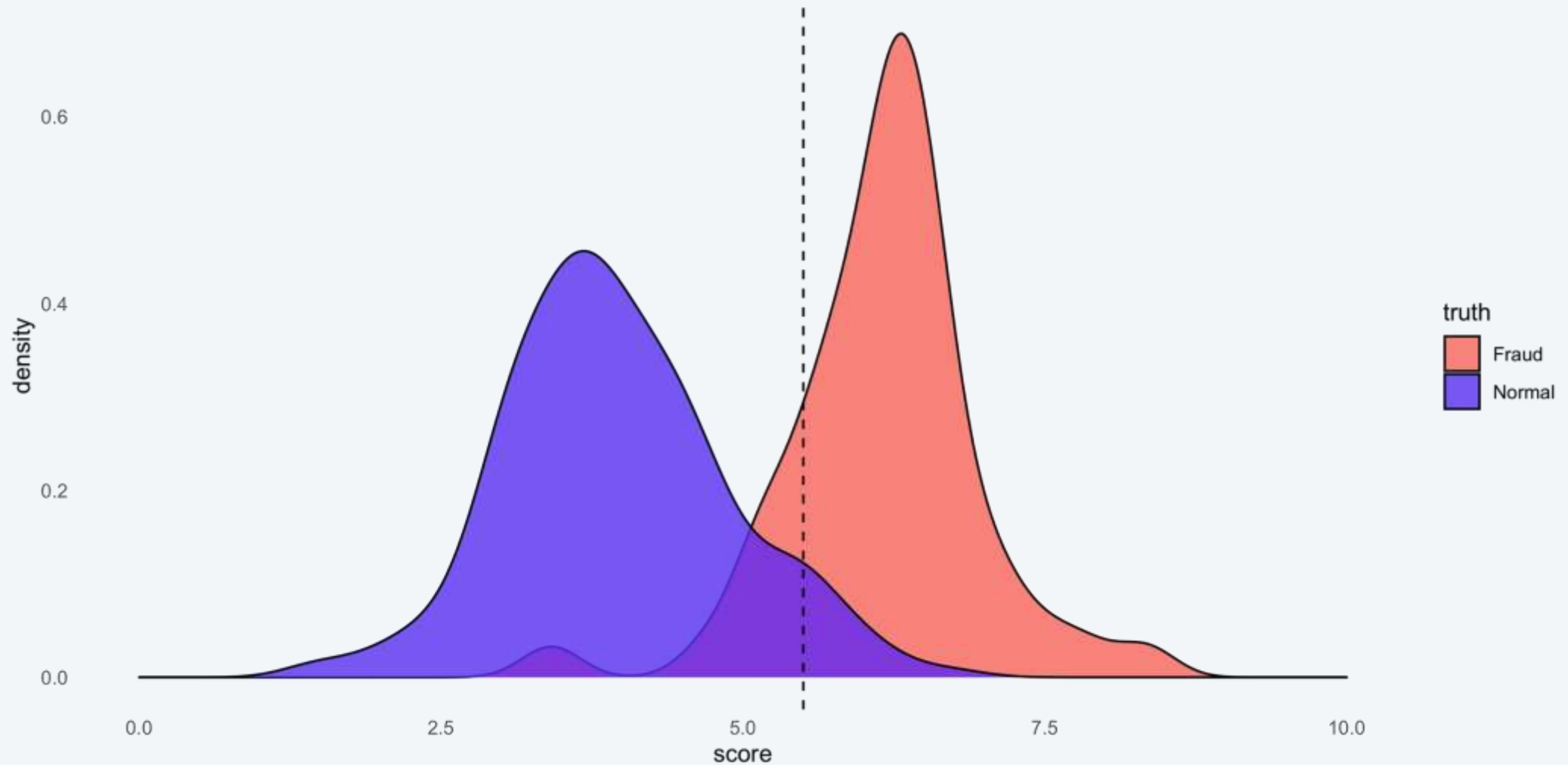
DATA SCIENCE IN OPERATIONS



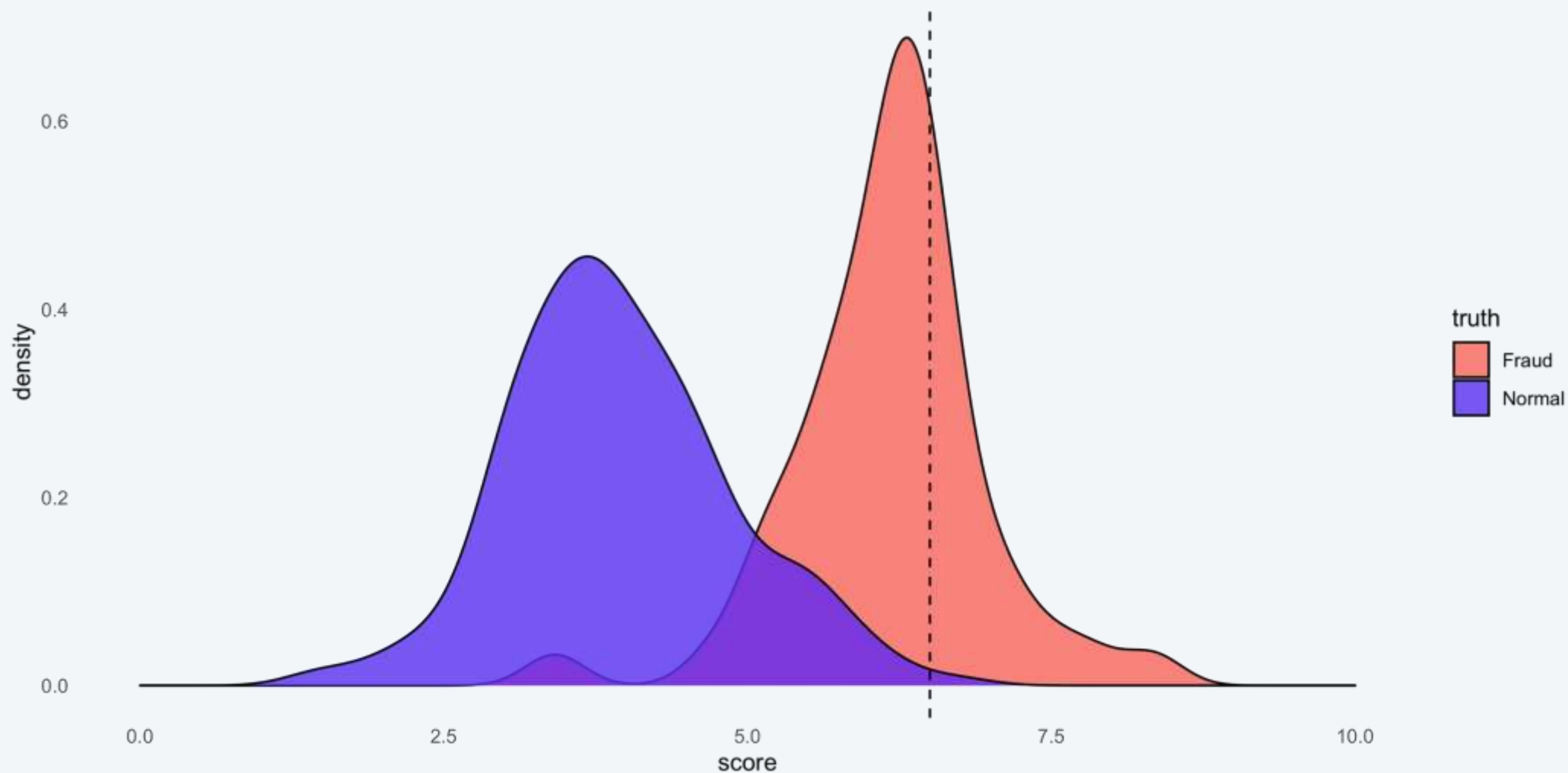
MODEL EVALUATION



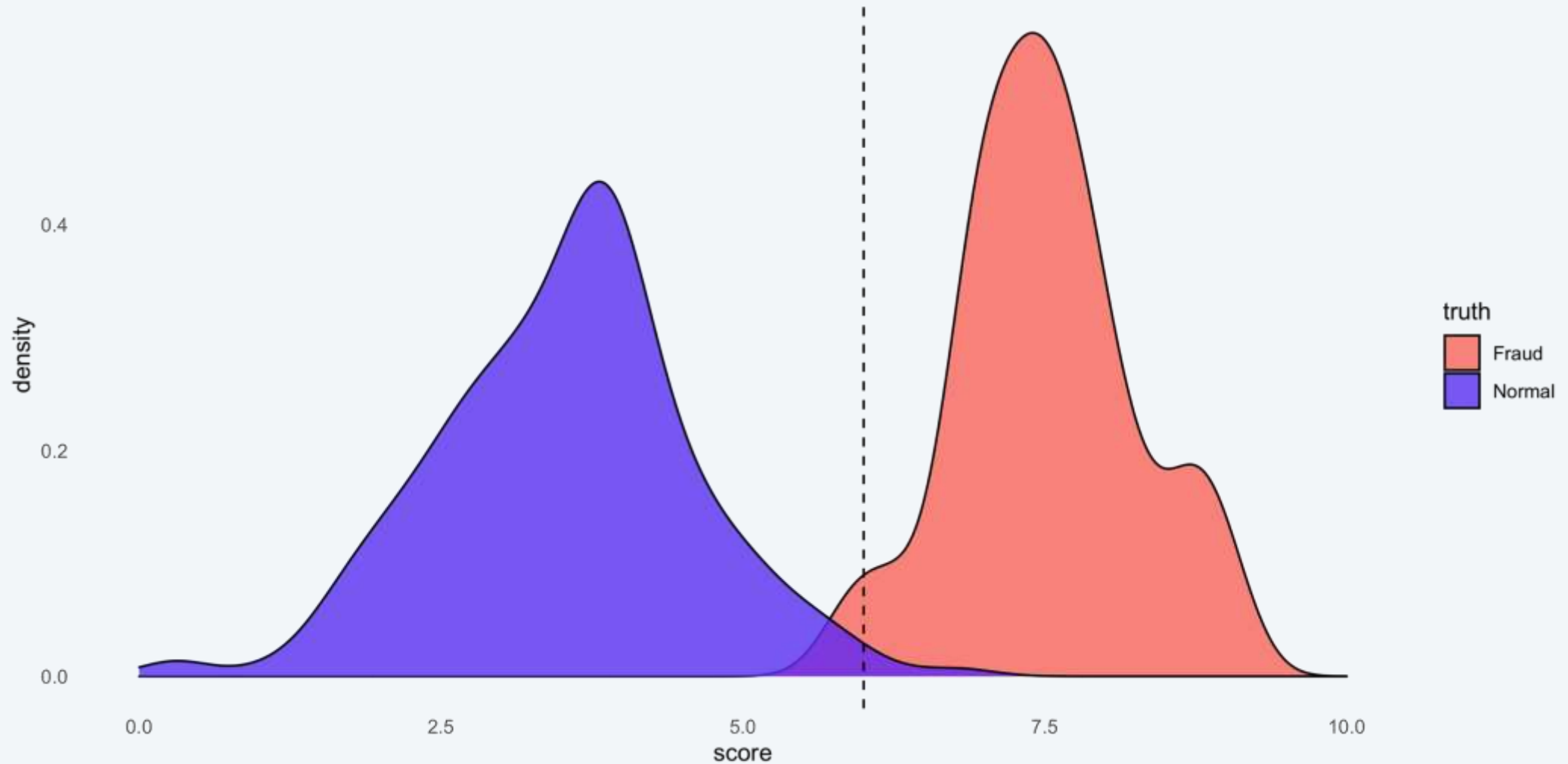
MODEL EVALUATION – WITH FEEDBACK



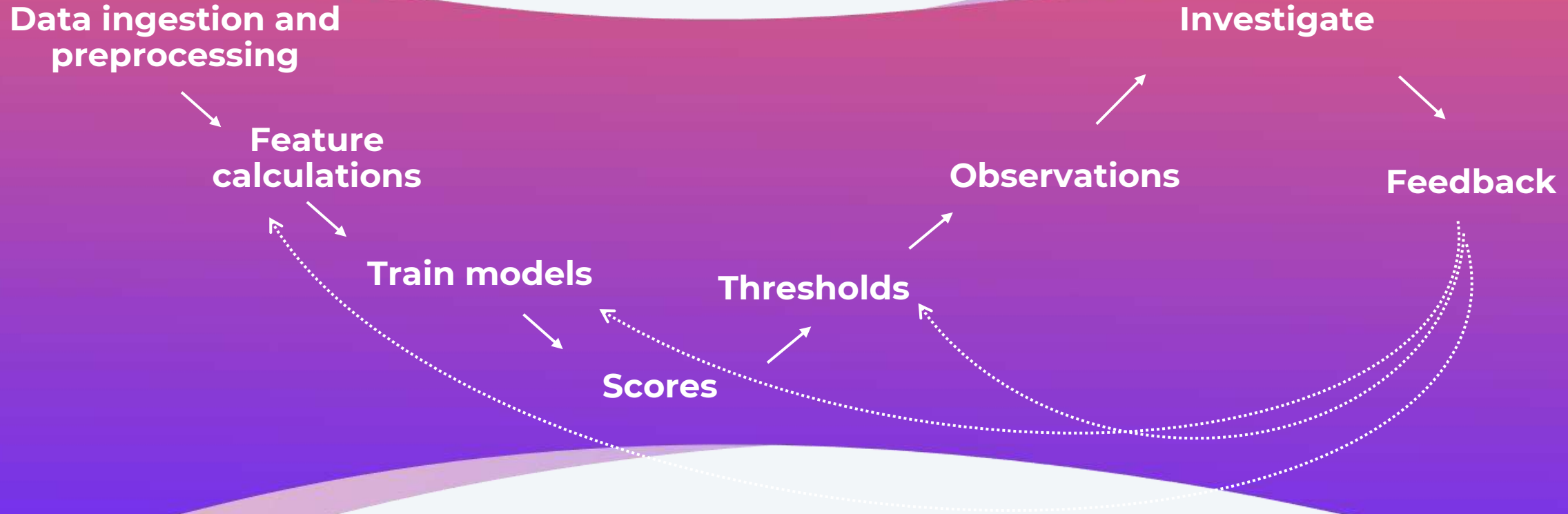
MODEL EVALUATION – UPDATE THRESHOLDS



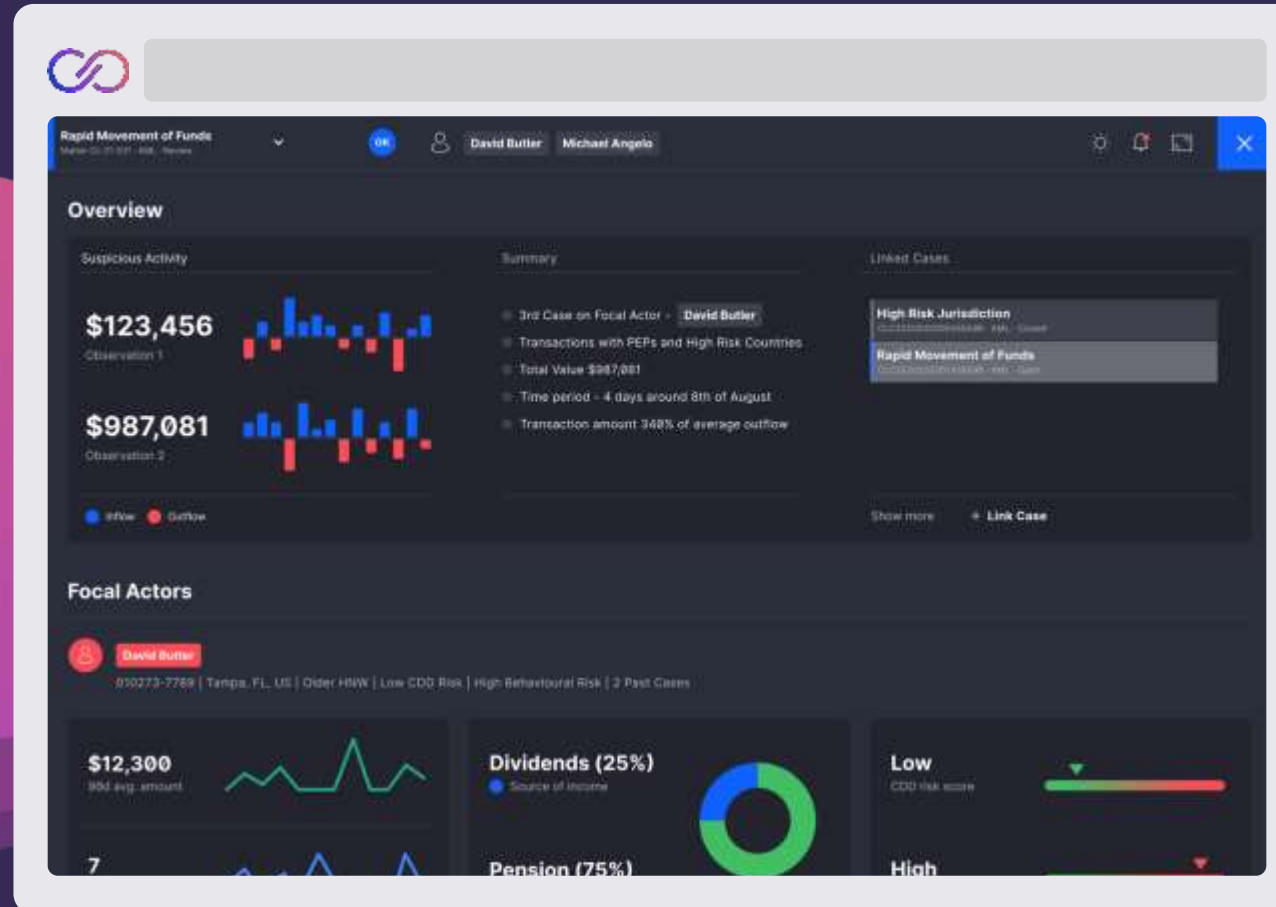
MODEL EVALUATION – UPDATE FEATURES & MODELS



DATA SCIENCE IN OPERATIONS CONTINUOUS IMPROVEMENT



EXPLAINABLE MODELS



EXPLAINABLE MODELS

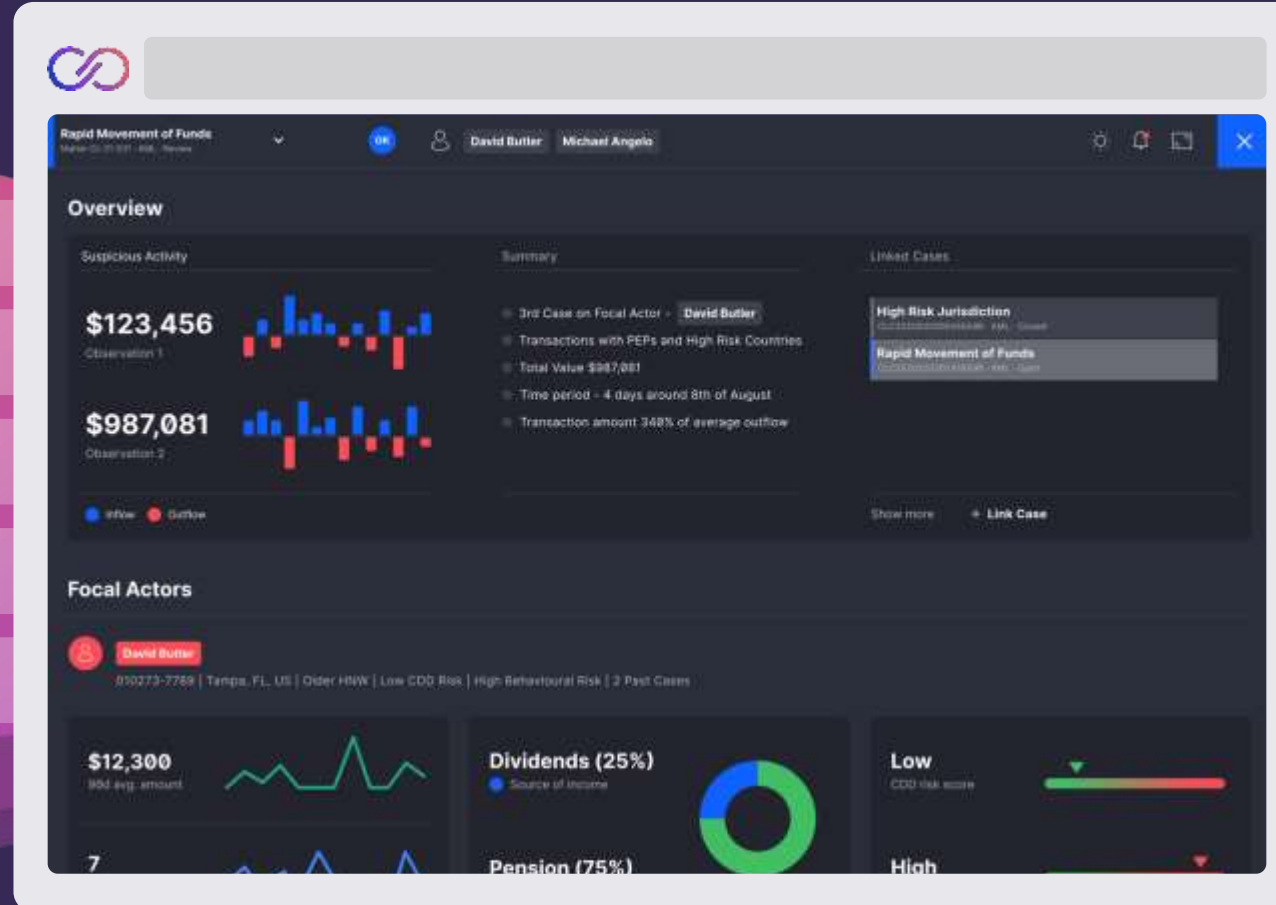
KYC Data

Risk and Credit Data

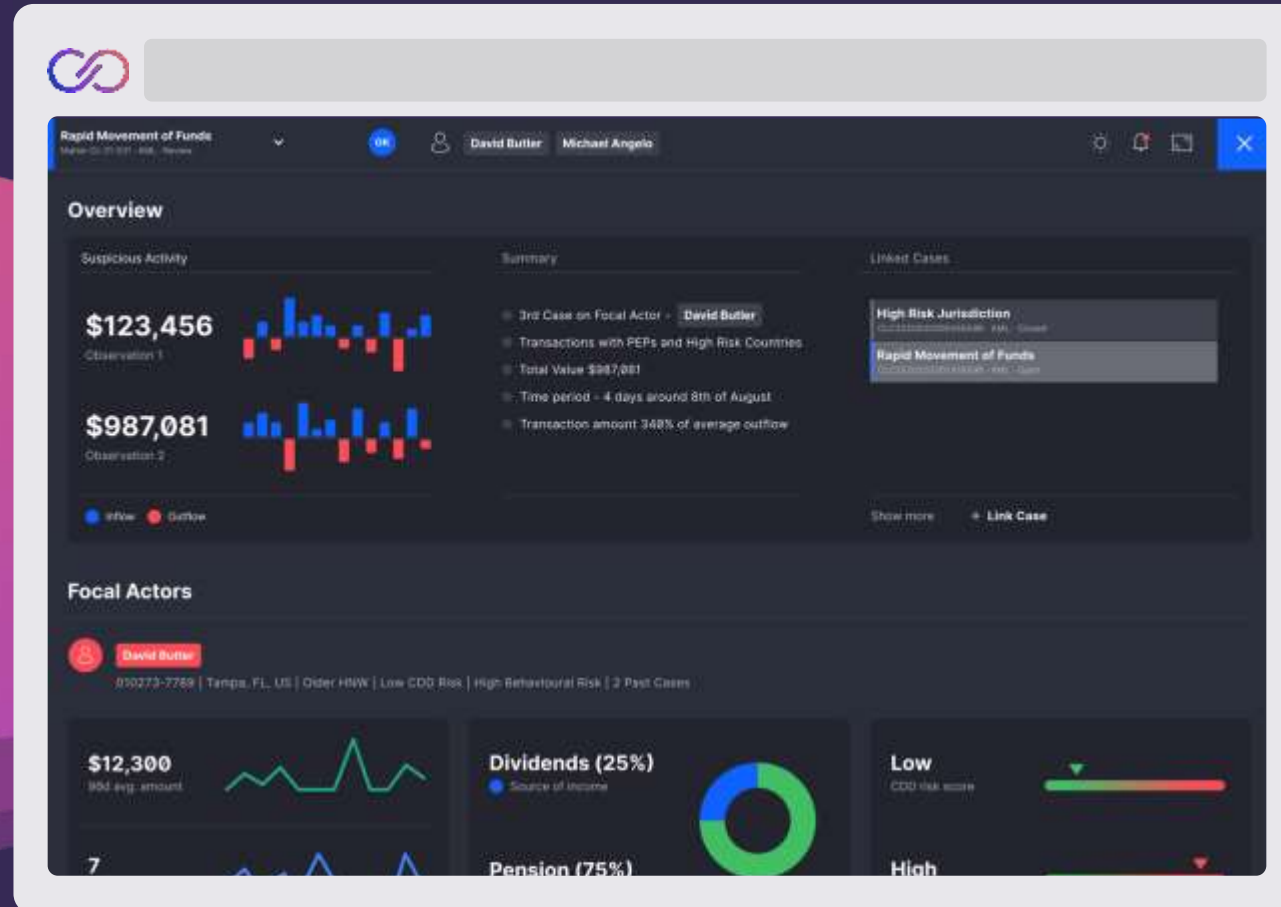
Fiat Transactions

On-chain Analytics

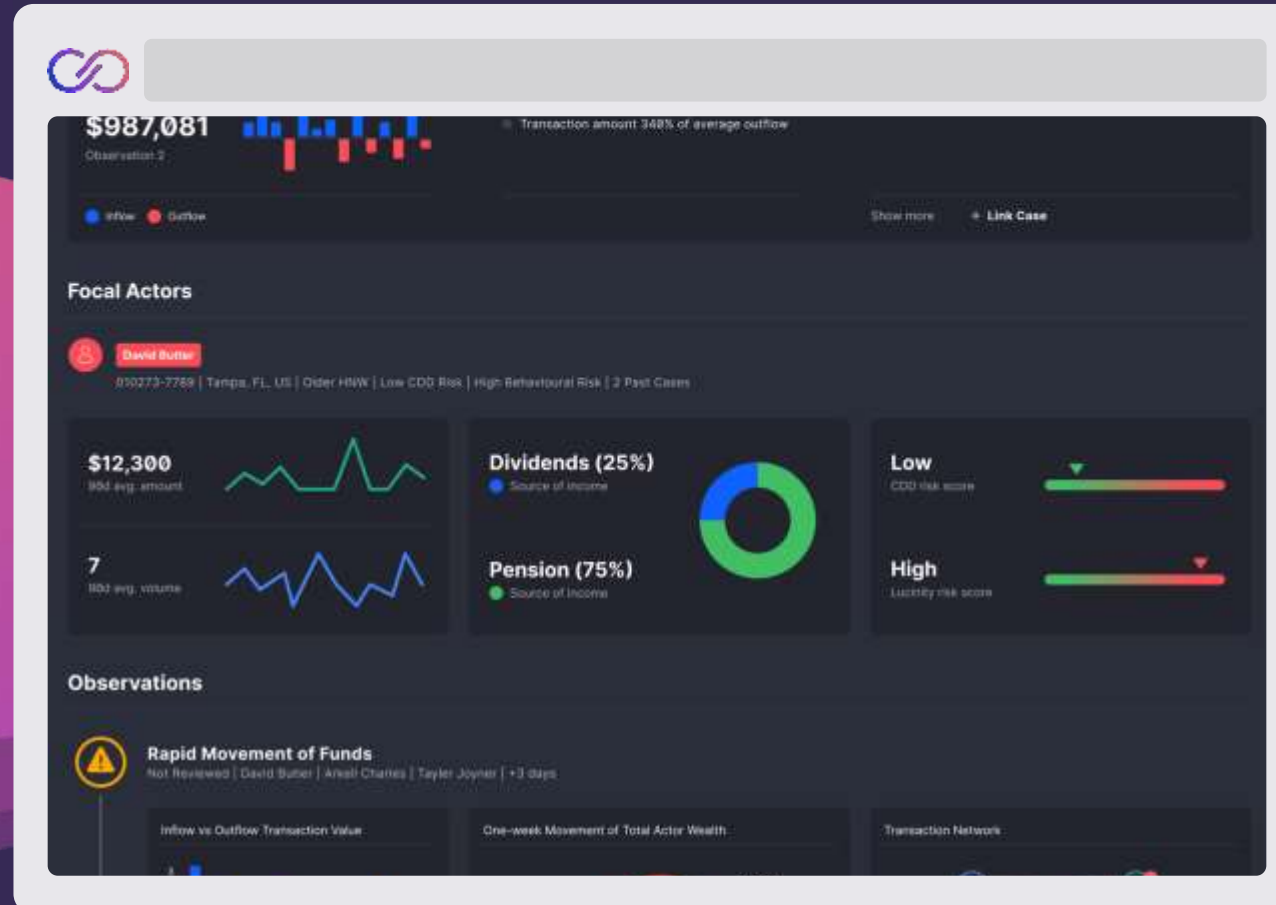
Open Banking Data



Stories



Actors





Observations



Rapid Movement of Funds

Not Reviewed | David Butler | Anesh Chanes | Taylor Joyner | +3 days

Inflow vs Outflow Transaction Value



One-week Movement of Total Actor Wealth



Transaction Network



The alerted activity occurred on April 11 for 24 days totaled **€667,061**. The activity consisted of **13 transactions** from David Butler, the focused actor to beneficiaries Taylor Joyner and Shellen Corp Inc.

Associated transactions by Date

06/04/2019, 11:22 AM	\$1,596.00	Deposit from Christian Russell an individual in IT	
06/04/2019, 11:22 AM	\$84.00	Deposit return from Anesh Butler an individual in RO	Risky Country
06/04/2019, 11:22 AM	\$42.00	Payment to Shellen Corp, a Legal Entity in IT	Public Person
06/04/2019, 11:38 PM	-\$6,654.00	Standing order to Larissa Ingram an individual in US	
06/04/2018, 11:41 PM	\$8,954.00	Rental income from Christian Russell an individual in IT	

HIGH RISK COUNTRY
Congo has a Base AML Index score of over 7, out of 100, while it has a Country score of 4.2 out of 5.

Behavioral insights



LUCINITY



Rapid Movement of Funds

Not Reviewed | David Butler | Arkadi Charles | Taylor Joyner | +3 days

Inflow vs Outflow Transaction Value



● Inflow ● Outflow

One-week Movement of Total Actor Wealth



● Inflow ● Outflow

Transaction Network



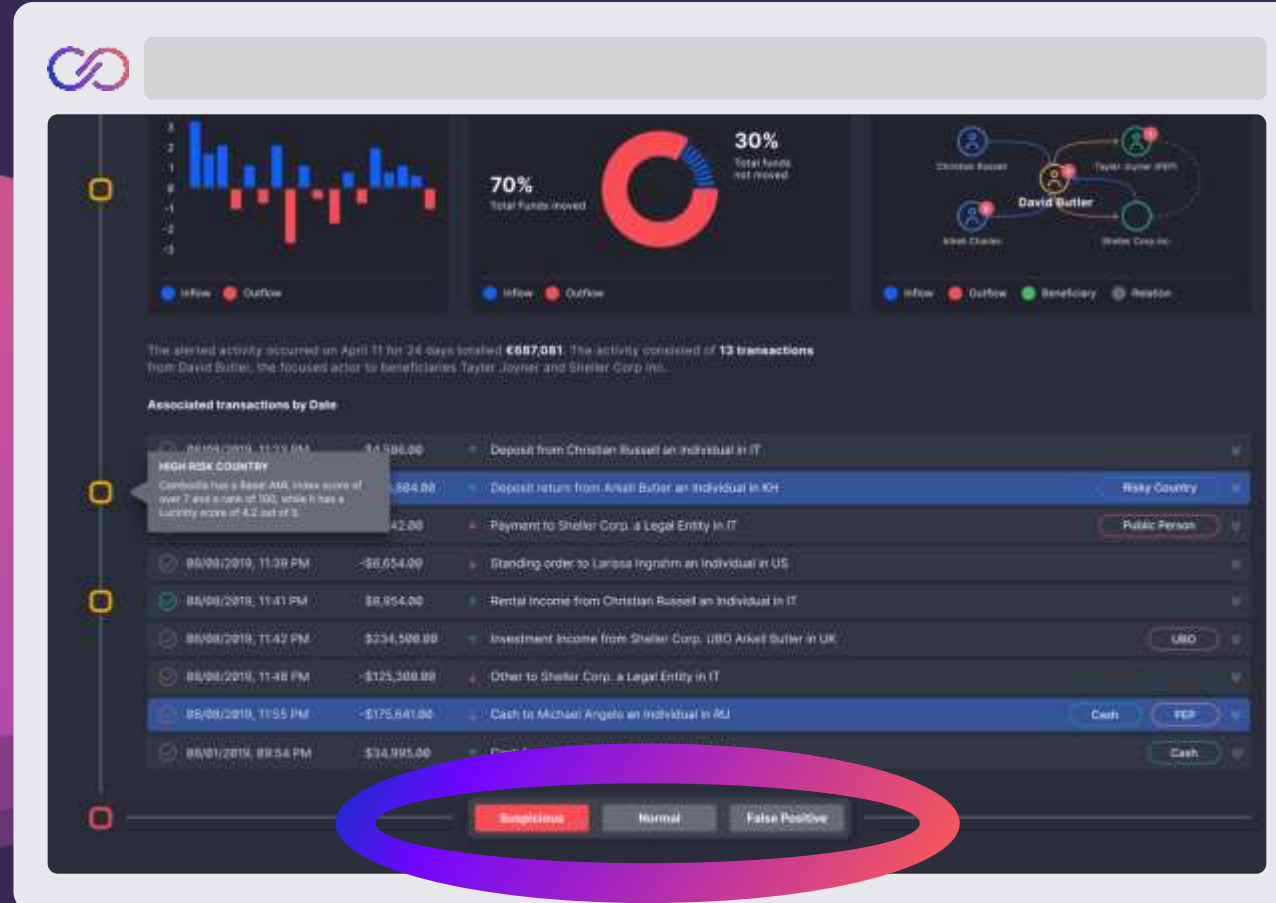
● Inflow ● Outflow ● Beneficiary ● Relation

The alerted activity occurred on April 11 for 24 days totaling **€667,081**. The activity consisted of **13 transactions** from David Butler, the focused actor to beneficiaries Taylor Joyner and Sheller Corp Inc.

Associated transactions by Date

08/09/2019, 11:23 AM	\$1,596.00	Deposit from Christian Russell an individual in IT	
08/09/2019, 11:23 AM	\$84.00	Deposit return from Arkadi Butler an individual in KOT	Risky Country
08/09/2019, 11:23 AM	42.00	Payment to Sheller Corp. a Legal Entity in IT	Public Person
08/09/2019, 11:39 PM	-\$6,654.00	Standing order to Larissa Ingram an individual in US	
08/09/2019, 11:41 PM	\$8,954.00	Rental income from Christian Russell an individual in IT	
08/09/2019, 11:42 PM	\$234,500.00	Investment income from Sheller Corp. UBO Arkadi Butler in UK	UBO
08/09/2019, 11:48 PM	-\$125,300.00	Other to Sheller Corp. a Legal Entity in IT	
08/09/2019, 11:55 PM	-\$175,847.00	Cash to Michael Angelo an individual in RJ	Cash FEP

HIGH RISK COUNTRY
Comodo has a Base AIO, index score of over 7 and a rank of 100, while it has a Locality score of 4.2 out of 5.



Continuous improvement
through
user feedback

That's how we operationalize data science
in the fight against money laundering
to create a better economy



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