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TECH

Challenges of KYC processes: A journey from screening a client to assessing its underlying network

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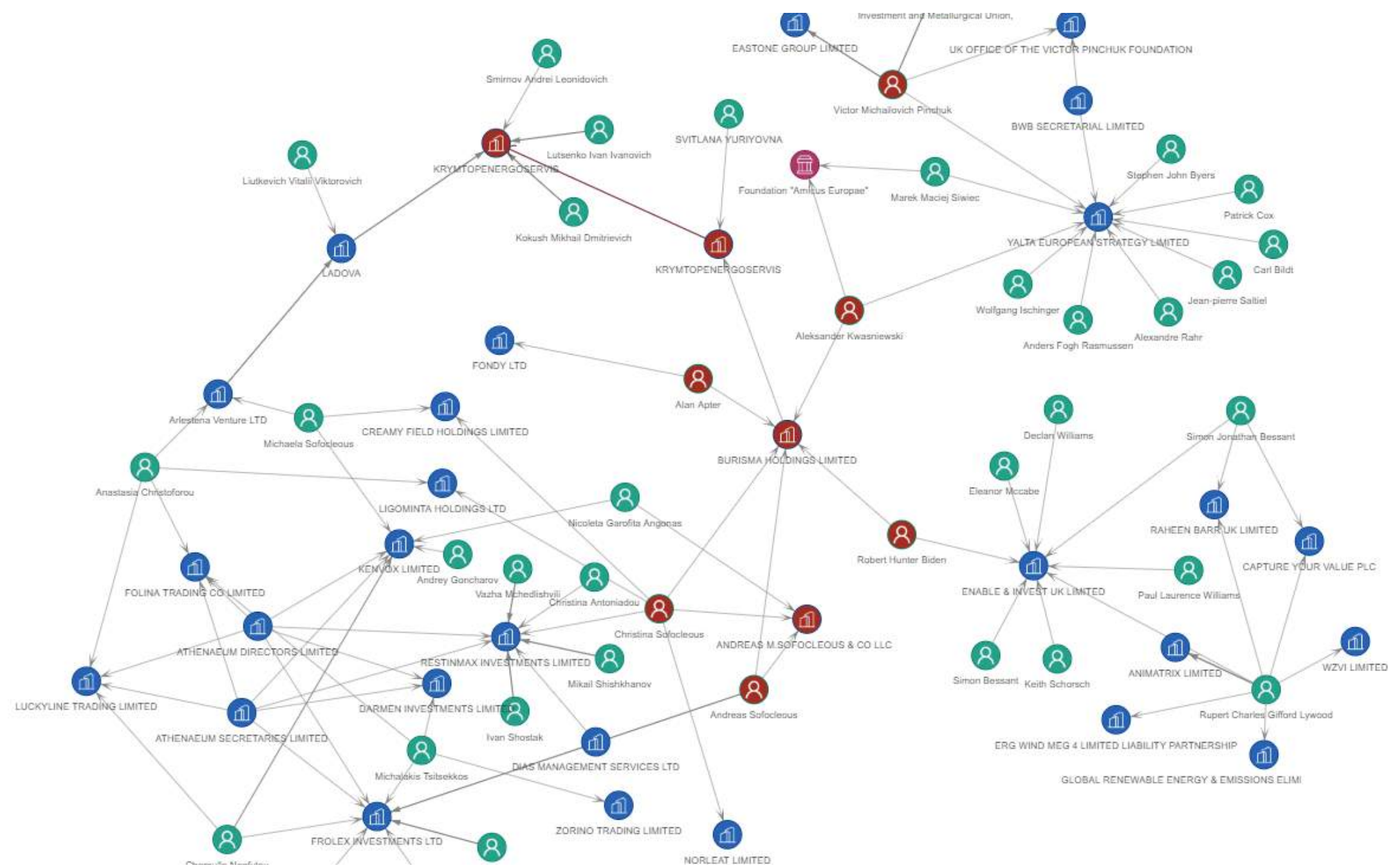
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Agenda

- ✓ Introduction
- ✓ KYC and Network-based approaches
- ✓ Challenges in screening global clients with Network-based KYC
- ✓ Building networks and data linkage
- ✓ How can Artificial Intelligence help?
- ✓ Q&A

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➤ Introduction

Introduction

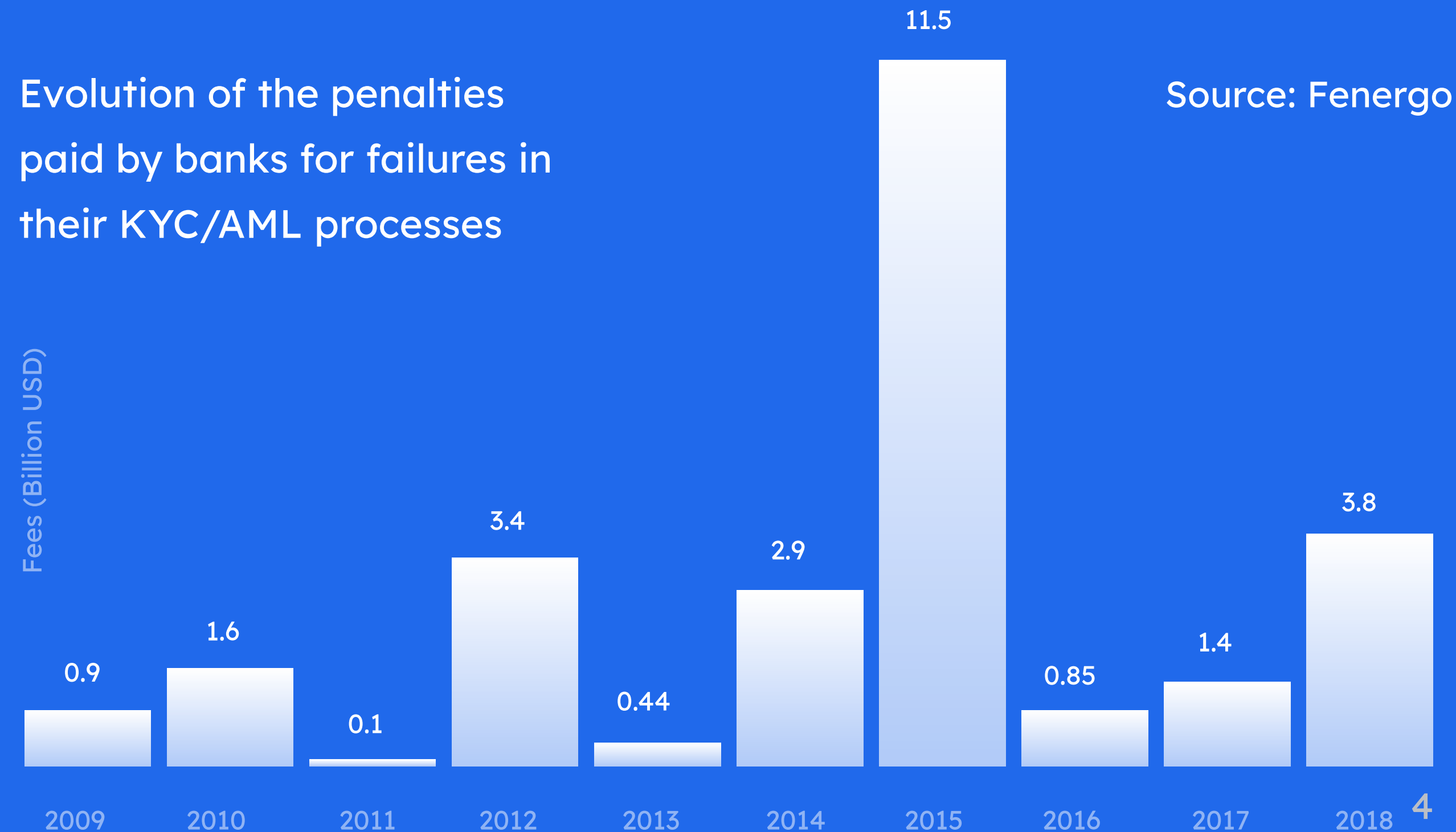
- ✓ Qualifying financial crime risk is becoming overly complex.
- ✓ Financial institutions are not able to discriminate “good” and “bad” clients.
- ✓ Current frameworks generate a high number of “false positives” and “false negatives”.

Institutions face a double-edged dilemma:

- Miss profits by being overly conservative or
- Pay penalties for being too aggressive

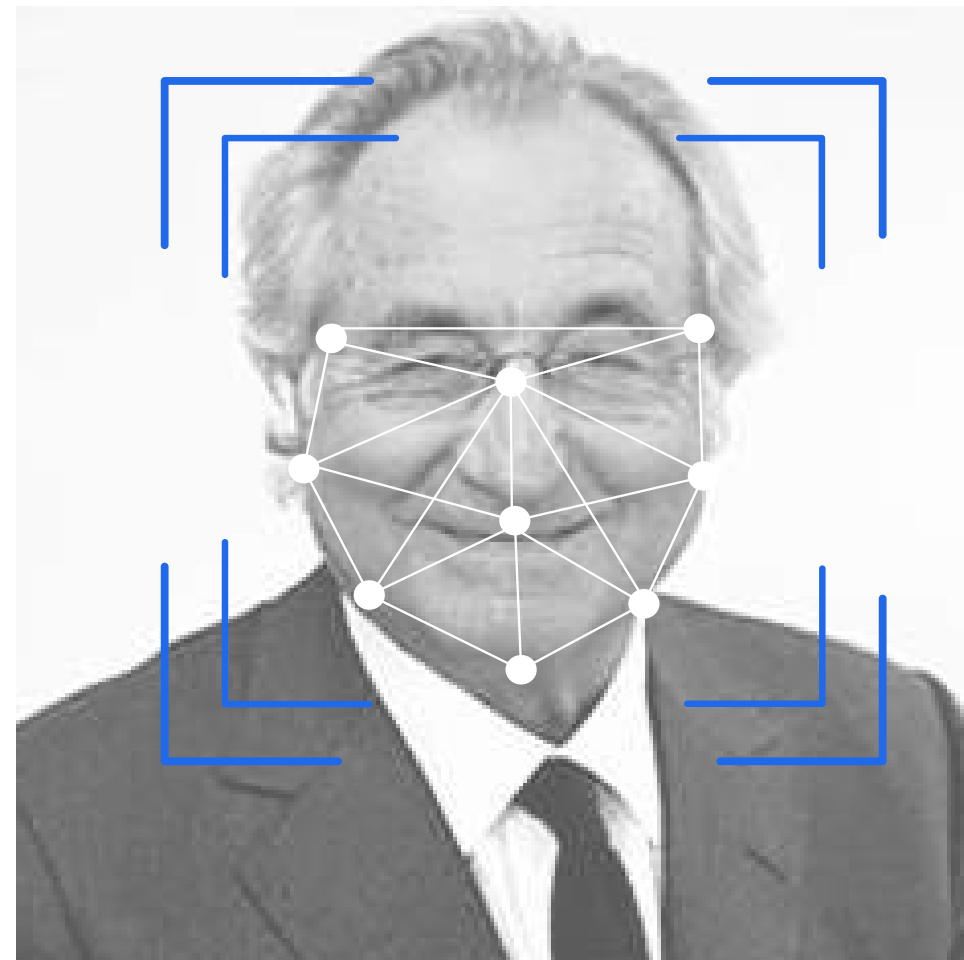
Evolution of the penalties paid by banks for failures in their KYC/AML processes

Source: Fenergo



What are the key components of **KYC**?

Initial screening



Identity verification

Client discovery process



Basic checks
Enhanced due-dilligence

Monitoring



Periodic checks
Customer activity

Client discovery process

- ✓ Convicted felons
- ✓ Ultimate Beneficial Owners
- ✓ Disqualifications
- ✓ Charges
- ✓ Insolvencies
- ✓ Sanctions
- ✓ Politically Exposed Persons
- ✓ Adverse media

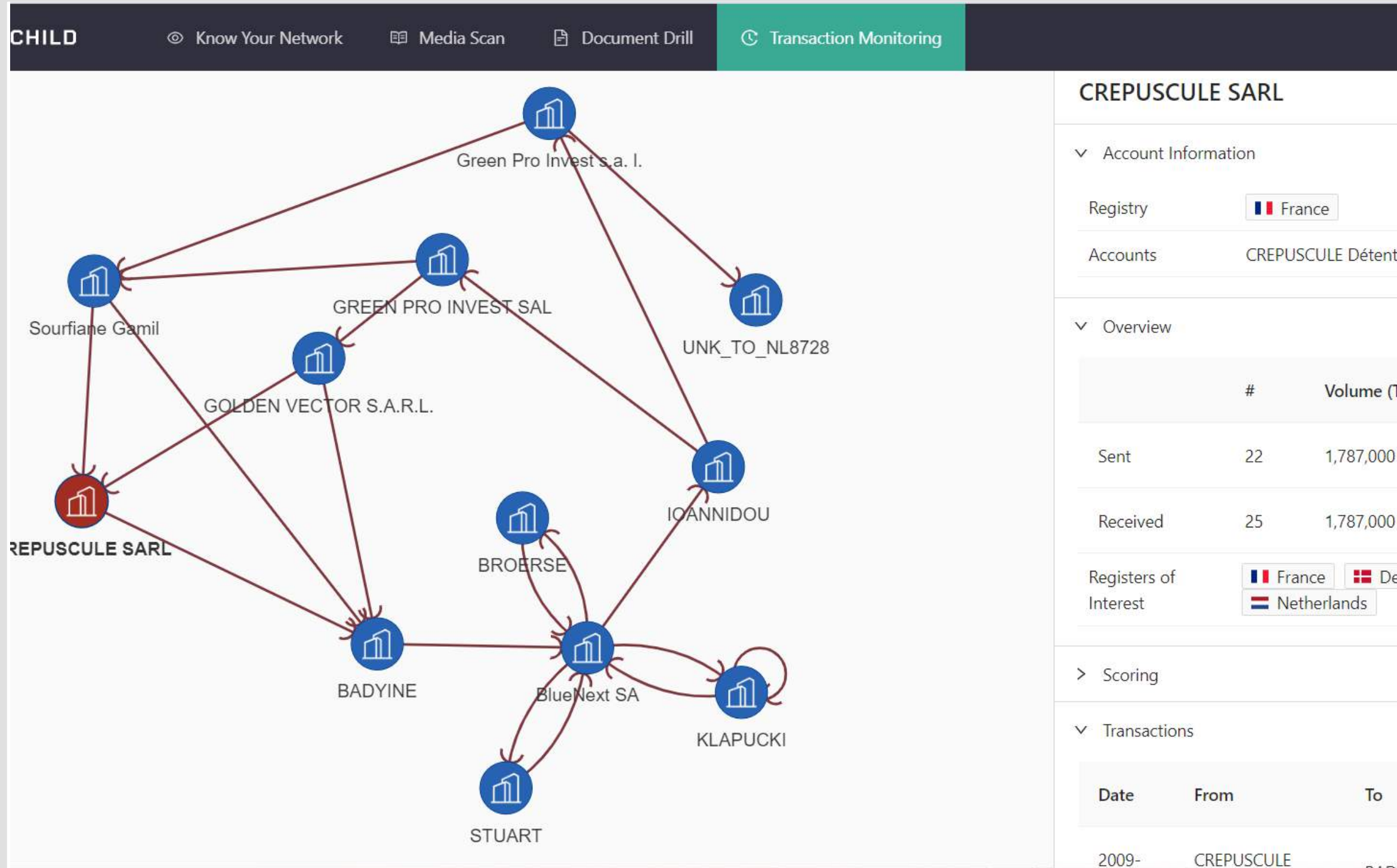


Are there “events” in the client’s past?

Is the identified client undesirable?

Does the client bear a high risk?

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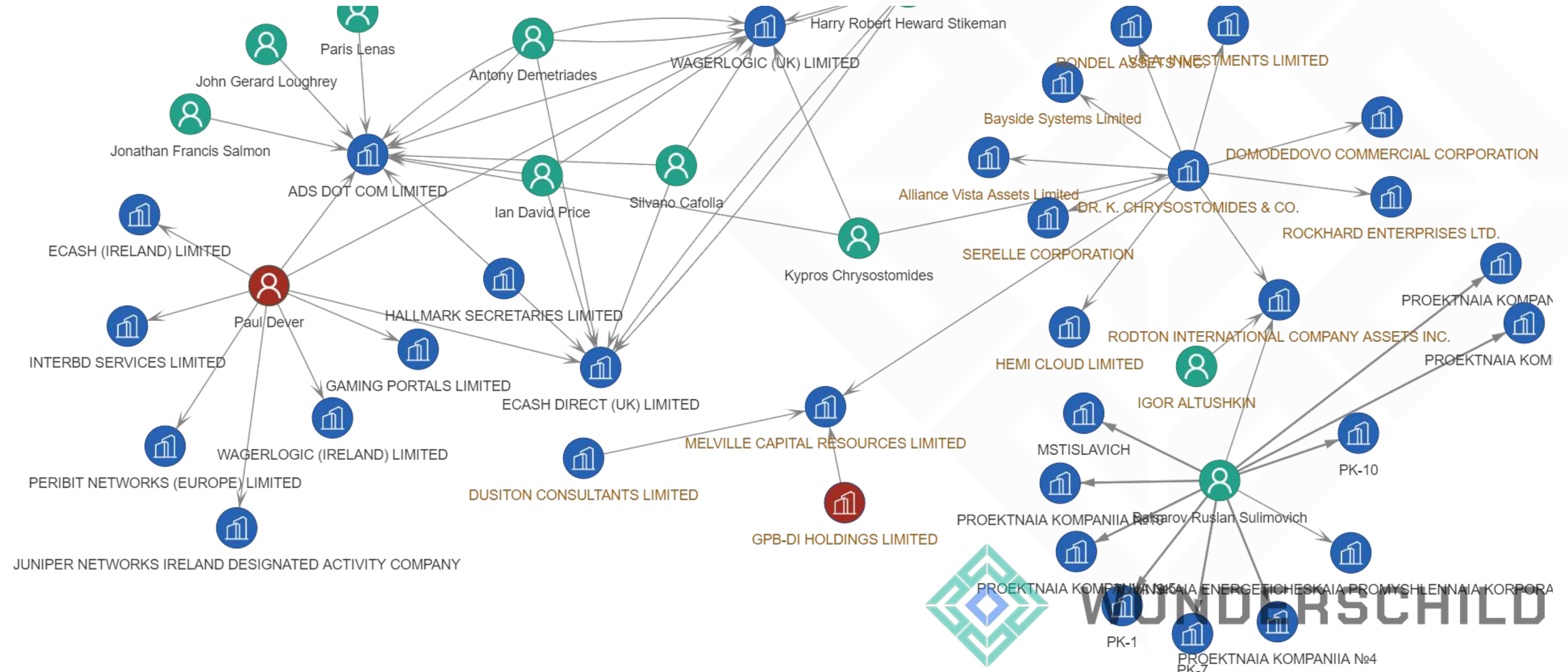


➤ **KYC and Network-based approaches**

KYC and Network based approaches

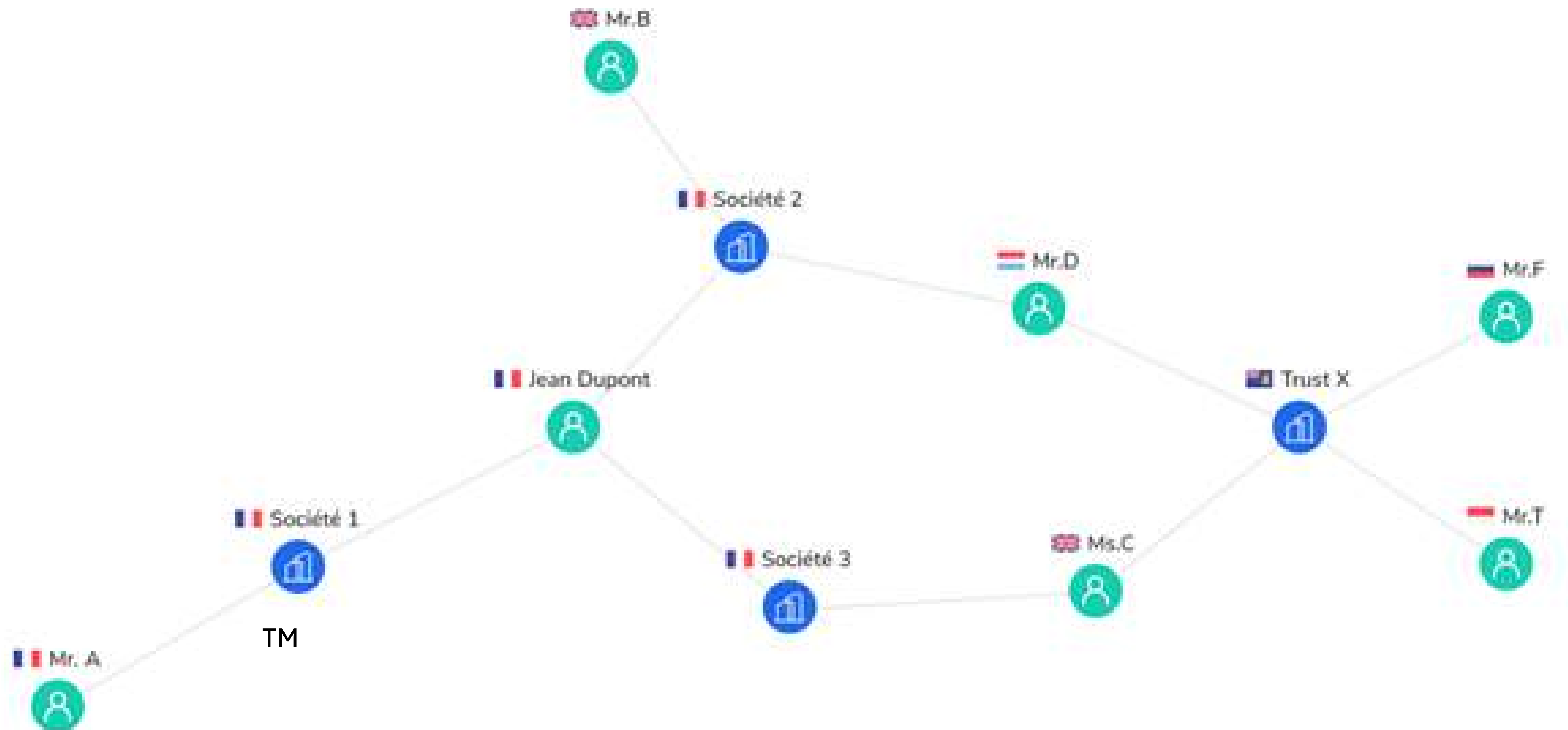
- ★ Assessing the **fully-fledged picture** of a client is a crucial aspect of the client discovery process.
- ★ A **plain standalone** client screening does not fully reflect the level of financial crime risk.
- ★ There is **never only one** person or one company behind a financial crime scheme, but an **organised network** of firms and individuals.
- ★ The basic KYC as a concept is **not efficient**, generates a high number of “**false positives**” and “**false negatives**” and cannot assess **criminal networks**.
- ★ A client can come as **low risk** through a plain screening. This process would not indicate whether the previous director of the client’s company is **disqualified** from another jurisdiction or has an investor who is related to a **sanctioned individual**.

Case study: Fincen Leaks/ICIJ/Sanctions



KYC and Network based approaches

Know Your Client's Network A paradigm shift from KYC



Network-based approaches new generation of compliance tools

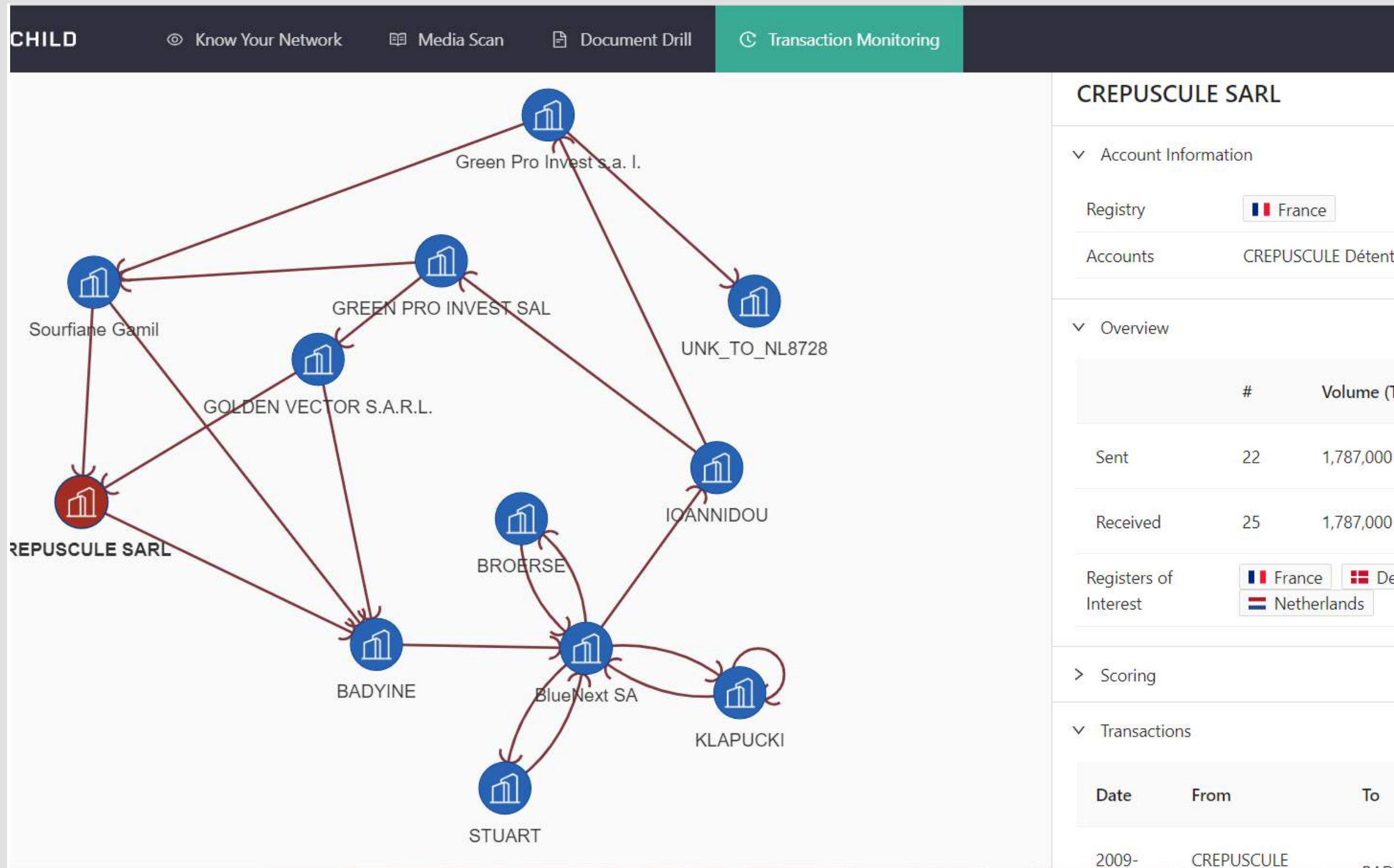
Knowing Your Client

- ★ Backwards-looking
- ★ Standalone approach
- ★ A high number of false-positive/negative
- ★ Siloed approach
- ★ Passive

Knowing Your Client's Network

- ✓ Forward-looking
- ✓ Focus on clients' connections
- ✓ Optimised performance
- ✓ Integrated approach
- ✓ Proactive

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➤ Challenges in screening global clients

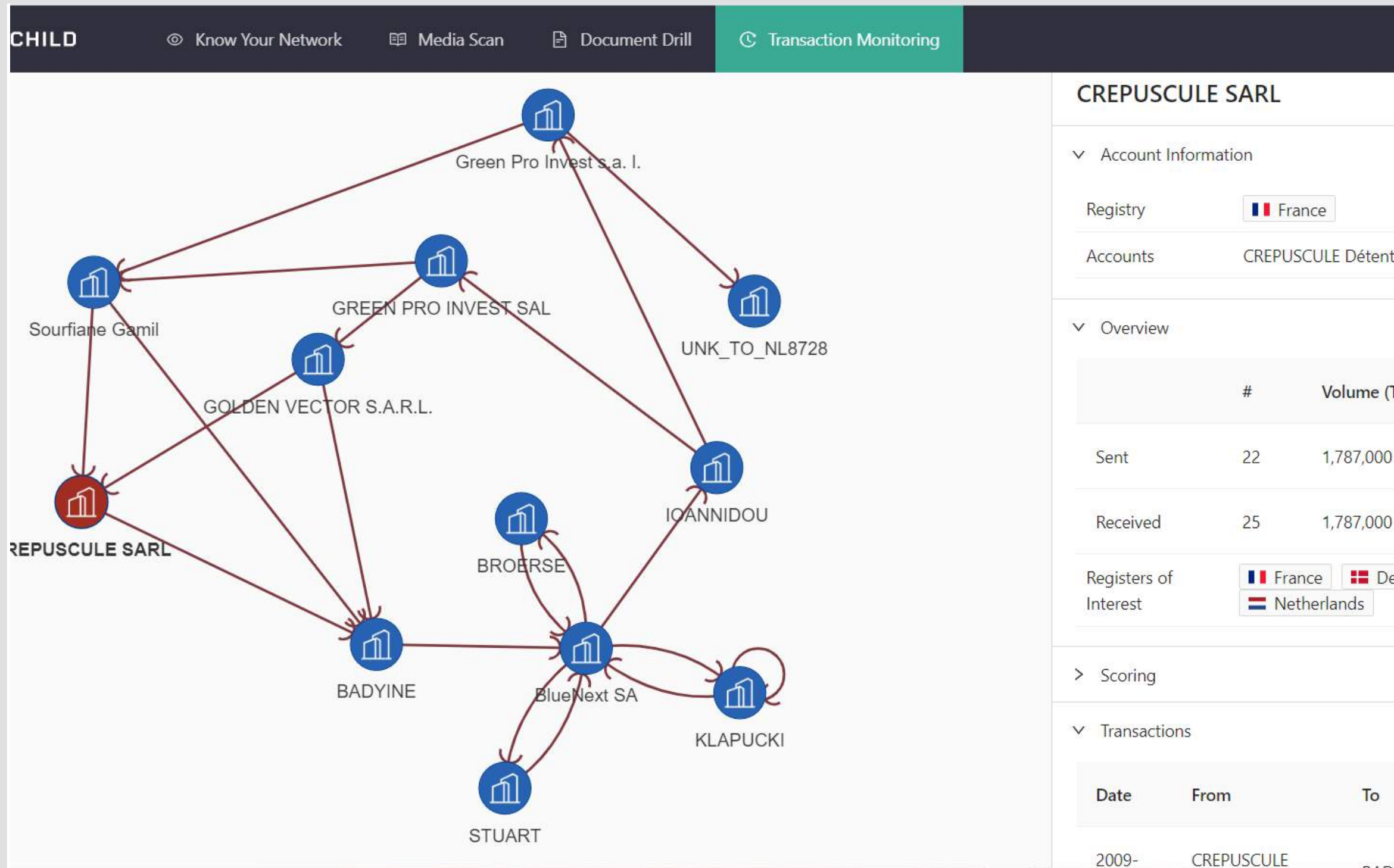
Challenges in screening global clients

- ✓ 5 AML Directive requires more transparency on **Ultimate Beneficial Ownerships** by setting up publicly available registers for companies, trusts and other legal arrangements.
- ✓ The network-based assessment becomes complex when the client **resides and owns assets in two or more countries**.
- ✓ The compliance officer needs to find all the records for such clients in **different databases and registries**.
- ✓ When dealing with clients having data recorded in **different languages and with different alphabets**, the simple name matching methods have severe limitations.

Screening global clients: data linkage

1. How to match two records with names in the **same language**?
2. How to match two records with names in **different languages** using the **same alphabet**?
3. How to match two records with names in **different languages** using **different alphabets**?
4. How to match two records of a person with a **very frequent name**?

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➤ Data linkage

Data linkage

Data linkage is the process of **finding records** in one or a few datasets that refer to the **same person or entity**.

Data linkage is necessary when joining datasets based on entities that may or may not share a **common identifier**.

The differences in data shape, language or format require **advanced algorithms**.

- ✓ ***Deterministic data linkage***: Links records by name and date of birth
- ✓ ***Probabilistic data linkage***: Matched only parts of the names/ translate in various languages
- ✓ ***Machine Learning data linkage***: Inferes relation-based rules from data

The most common strategies for data linkage are:

- ✓ **Name matching**, consisting of simple entity name matching (*Deterministic*)
- ✓ **Name + Personal Info (PI) matching**, consisting of entity name matching and matching of entity related information (Address, Gender, Date of Birth) (*Deterministic/Probabilistic*)
- ✓ **Names + Personal Info (PI) + Relational Info (RI)** (ie. connected entities) matching, consisting in name matching, matching of entity-related information and matching of connected entities names (*Probabilistic/Machine learning*)

Multilingual name matching

Name transliteration in
different languages:



Risks

Hide past events

Create synthetic identities

English: Mustafin Ilgiz Aivarovich

Russian: Мустафин Ильгиз Айварович

French: Moustafine Ilguiz Aïvarovitch

German: Musstafin Ilgis Aivarowitsch

Hebrew: מוסטפין אילג'יז אייברוביץ

Multilingual name matching

- ✓ Similarity functions are left **undefined** for the cases where names are represented as one string, and it is unknown how to **separate names** into parts (first name, last name, etc.).
- ✓ Jaro-Winkler and Levenshtein distances give **maximum distances** for strings written in **two different alphabets** (e.g. Latin and Cyrillic). This also limits the applicability of the approach in multi-lingual context, and increase the **dependency on the transliteration model** used.
- ✓ The **solution** is to convert name strings to some **common phonetic representation** of the names and then to compare the phonetic representations. Some of the possible phonetic representations are Soundex, Match Rating Approach, Daitch-Mokotoff Soundex, Beider-Morse Phonetic Matching, Double Metaphone.
- ✓ After the names are converted to **their phonetic representations**, the two strings can be compared using a similarity metric.

Case Study: French - Russian

French: Gérard Xavier Depardieu



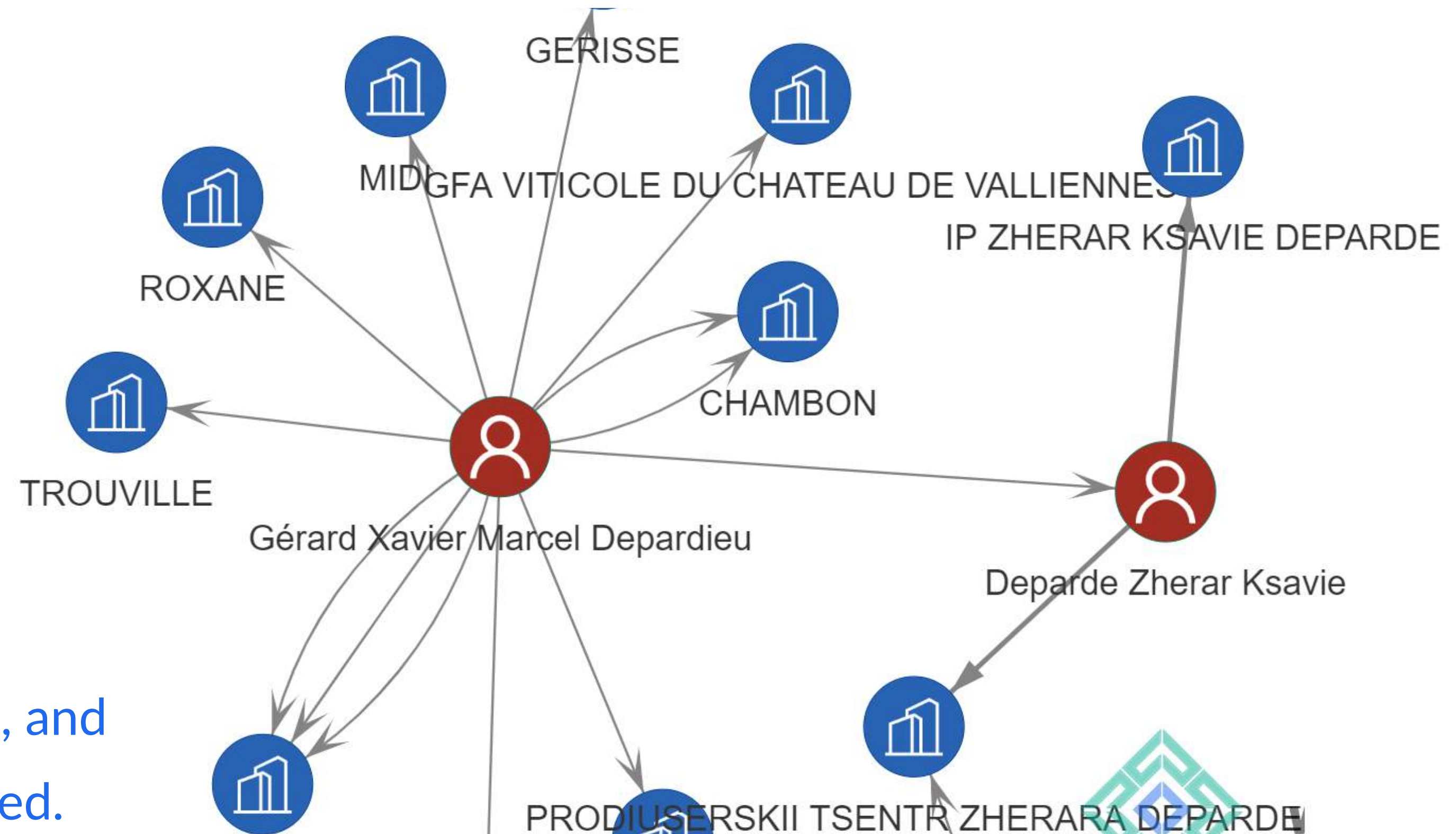
Russian: Жерар Депардьё /
Жера́р Ксавье́ Депардьё



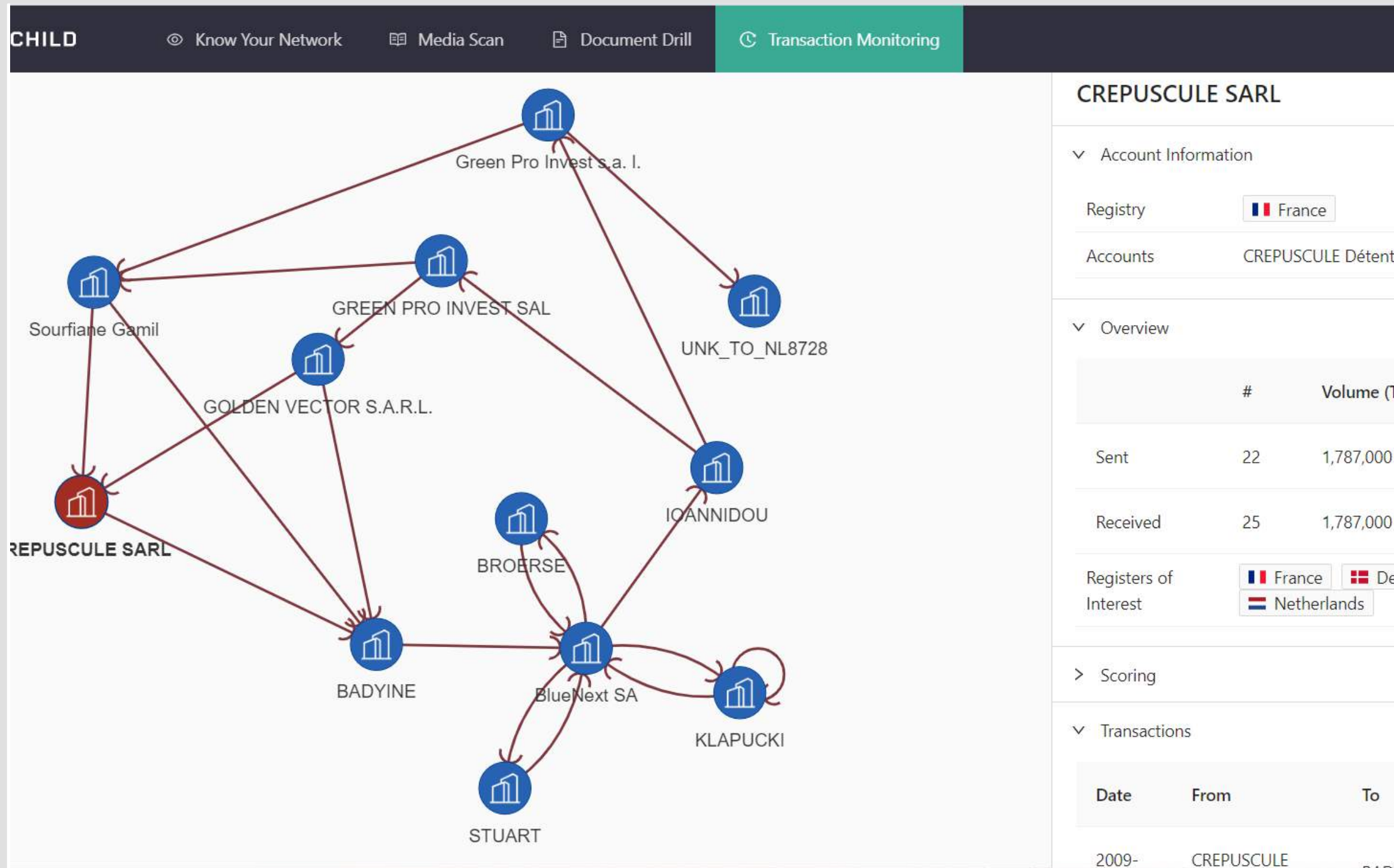
English: Zherar Ksavie Deparde

The two versions of the name are hugely different, and in fact, in such a situation another identity is created.

Transliteration is a real weapon facilitating the creation of multiple identities



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➤ How can Artificial Intelligence help?

What does AI mean?

Artificial intelligence (AI) refers to a set of methods and systems aiming **to simulate human intelligence**. AI is implemented in machines that are programmed **to think like humans and mimic their actions**. In compliance, the use of AI encompasses three levels of complexity:

1. Automation of **repetitive manual task** (i.e. search, box-ticking processes)
2. Emulation of **human logical reasoning** (i.e. replication of rule-based actions, implementation of syllogisms)
3. Origination of **new rules and reasonings** based on data exploration with machine learning techniques

How can Artificial Intelligence help?

- ✓ Automate **simple name matching process**, when names are in the same language (**Level 1**).
- ✓ Automate **data linkage** based on name matching and DOB (**Level 1**).
- ✓ Execute **relational-attribute based matching** approaches. AI systems can explore the client's connections and match based on common relationships (**Level 2**).
- ✓ Execute relational-attribute based matching approaches using data from Adverse media. **Named Entity Recognition** (NER) techniques can help to enforce matches (**Level 2**).
- ✓ Assess the **risk** of a client using information driven for clients's network (**Level 3**).
- ✓ Integrate **screening** and **transaction monitoring** (**Level 3**).

What are the technologies available for Network-based KYC?

	Popularity	Speed	Scalability	Data management	AI
	★★★★	★★★	★★★	★★★	★★★
 Amazon Neptune	★★	★★★	★★★	★★★	★★★★
 TigerGraph	★★	★★★★	★★★★	★★★★	★★
 OrientDB®	★★★	★★	★★★	★★★	★
 ArangoDB	★★★	★★★	★★★	★★★	★★

What are the challenges?

- ★ **Implementation:** Deploying AI systems to enhance compliance functions is a **long and intense process**.
- ★ **Legacy systems:** AI works better when data repositories are mapped and standardised. Legacy data warehouses require, in most cases, **massive re-engineering** to serve efficiently AI.
- ★ **Scalability:** AI may work well when applied to the regional compliance function, but maybe **sub-optimal** in terms of speed and performance when deployed to **bigger scale** (i.e. screening hundreds of thousand vs hundred of million clients).
- ★ **Cost:** Implementing AI in global financial institutions incurs **high expenses** and impact budgets over several years.

How can Artificial Intelligence help?

- Box-ticking regulatory driven solutions are less concerned about performance
- Legacy solutions are not cost-effective and require consistent staff expenses
- R&D fuels the high performance

Network-based
KYC solutions

Network-based,
multi-lingual entity
resolution driven and AI
enhanced KYC solutions

“Box-ticking”
solutions

“Box-ticking”
solutions +AI

Performance

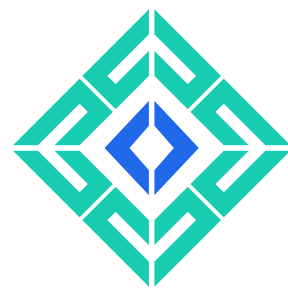
Total Value of
Ownership

Performance = Risk discrimination capacity (Low false negatives + false positives)

Total Value of Ownership = Savings due to process automation + Gains due to opportunites losses - product cost

Q&A

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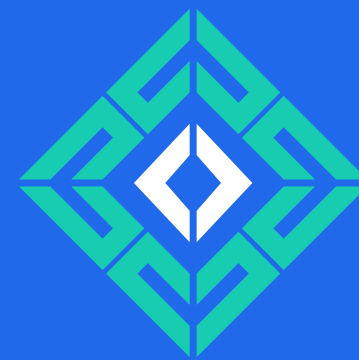
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Introduction



- ✓ Founder of **Schwarzthal Tech**: AI-driven platform providing financial crime intelligence
- ✓ Ex - commodity broker, risk management and compliance consultant
- ✓ Expert for the **European Parliament** on topics like VAT fraud, AML and CTF
- ✓ Expert evidence in **courts proceedings** for financial crime cases

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Expert witness

