Detecting money laundering transactions with machine learning

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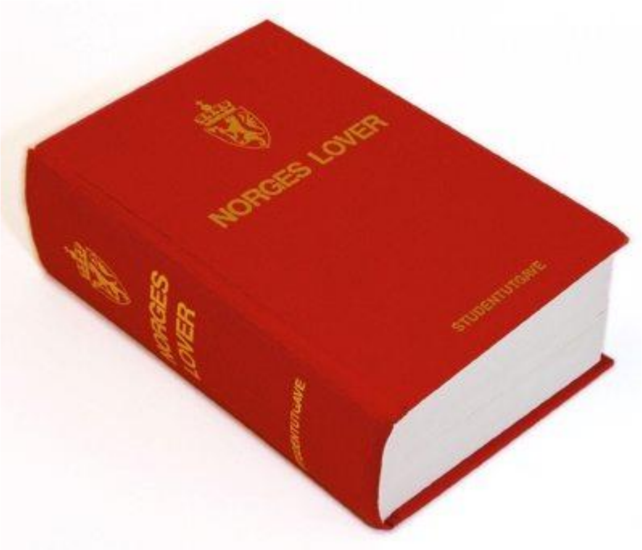
Money laundering

- Making money from criminal activity appear legal
- Examples
  - Buy antics with dirty money –
    state as attic finding –
    sell legally
  - Incorporate criminal funds in your own legal business

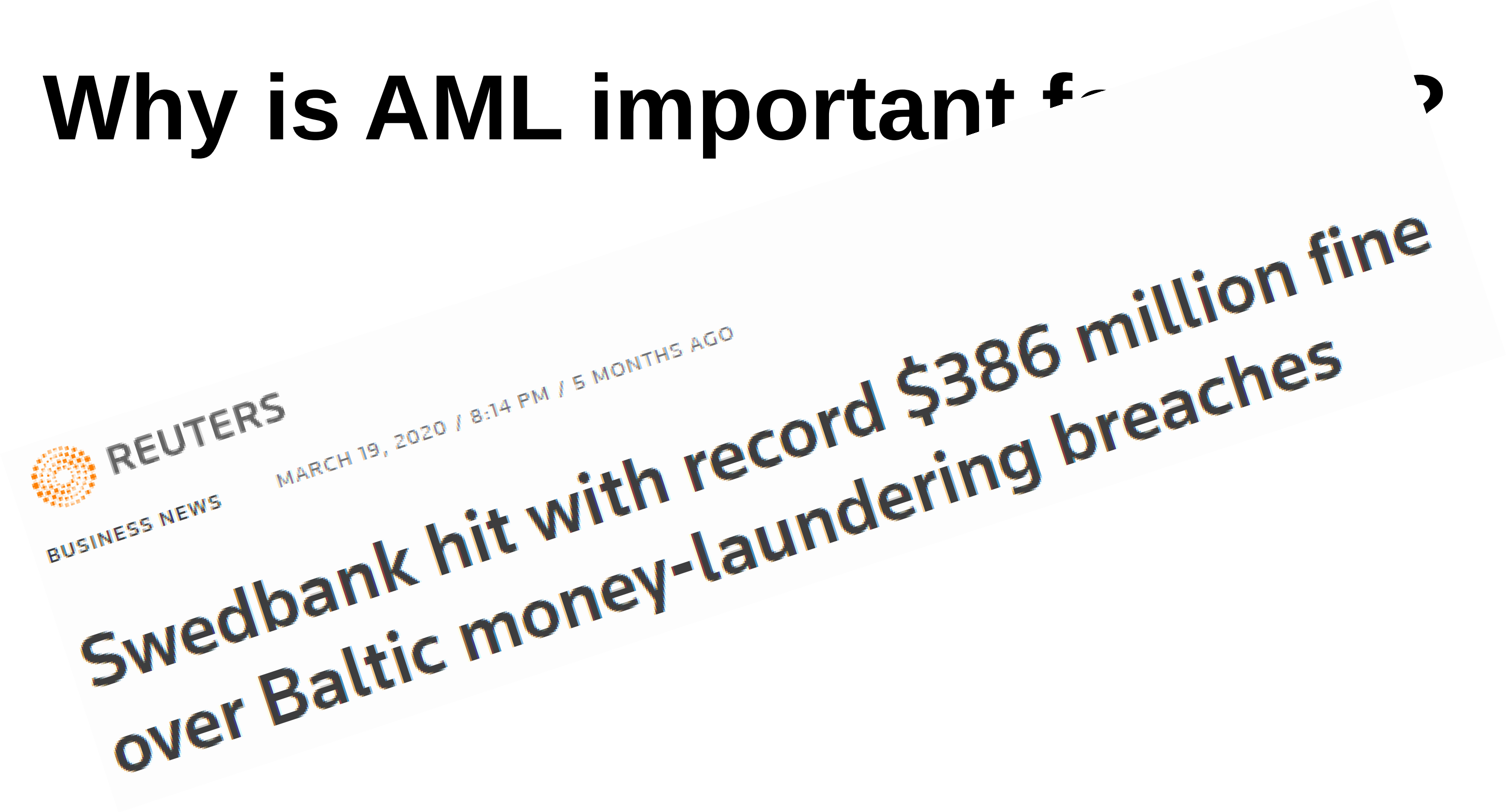
Money laundering



- Making money from criminal activity appear legal
- Examples
  - Buy antics with dirty money –
    state as attic finding –
    sell legally
  - Incorporate criminal funds in your own legal business

- All financial institutions are legally binded to report “suspicious transactions” to Økokrim

Why is AML important f ?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Swedbank hit with record $386 million fine over Baltic money-laundering breaches

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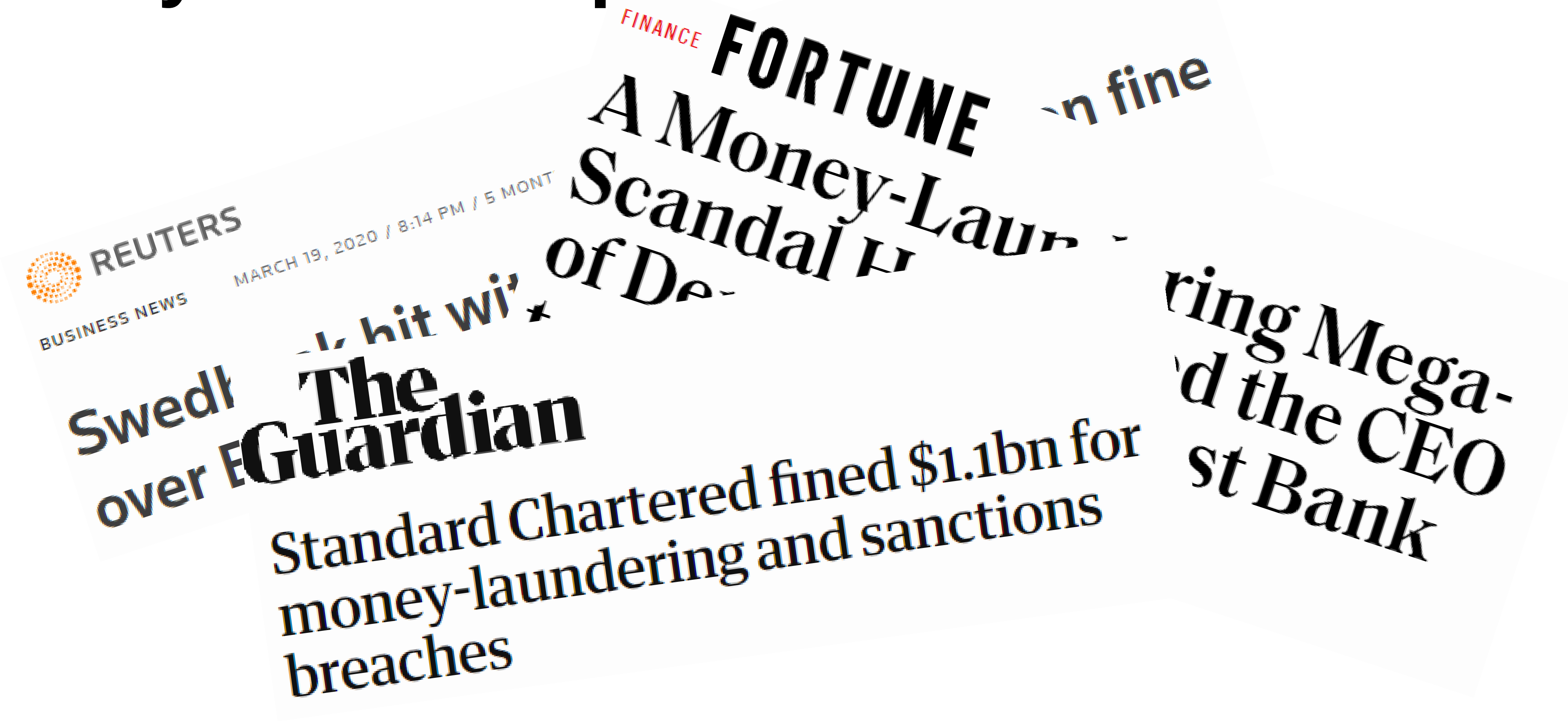
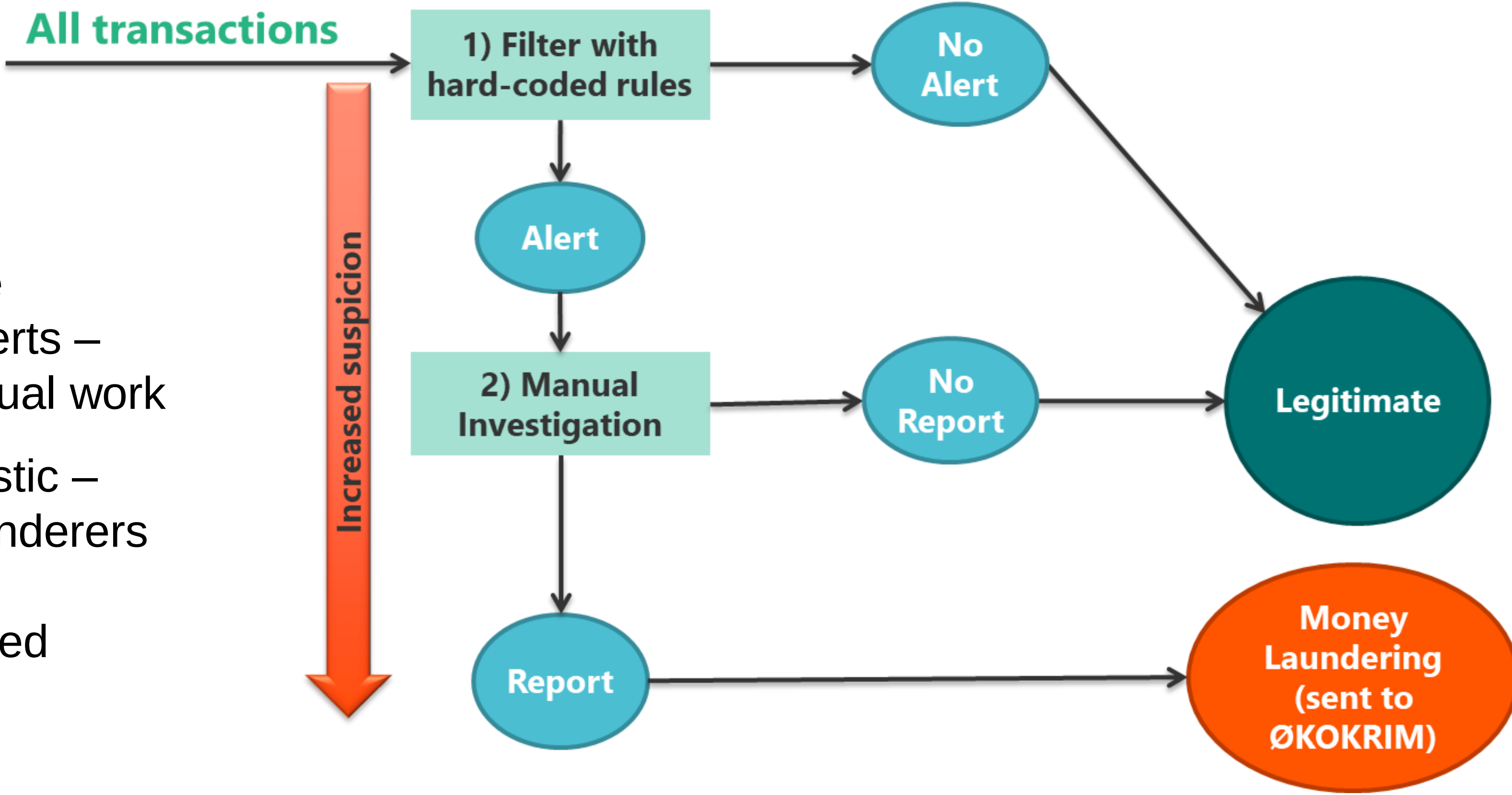
A Money-Laundering Mega-Scandal Has Forced the CEO of Denmark's Biggest Bank to Resign

Why is AML important



Current AML process at DNB

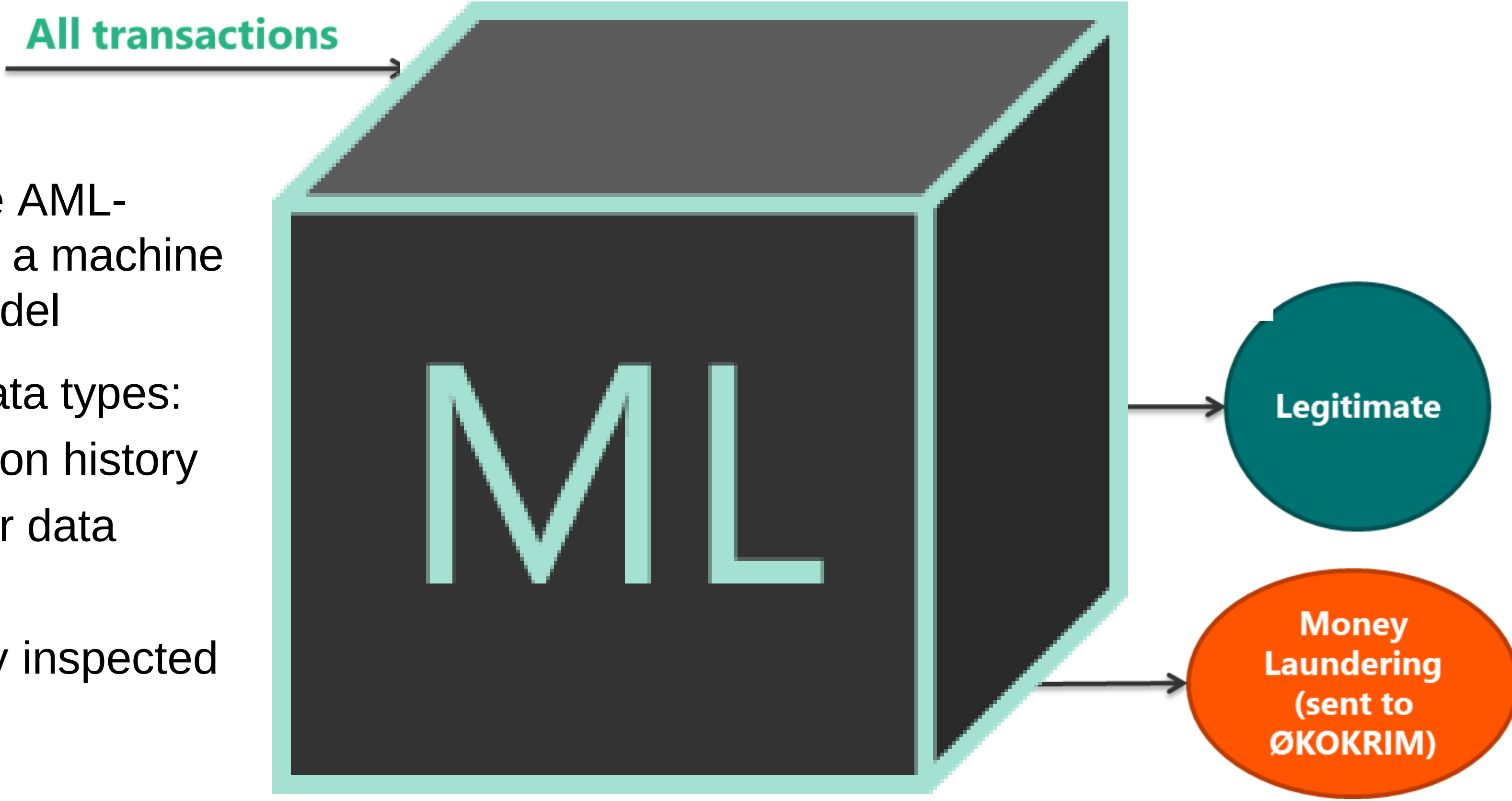


Weaknesses

- Many false positive alerts – much manual work
- Too simplistic – Money launderers are more sophisticated

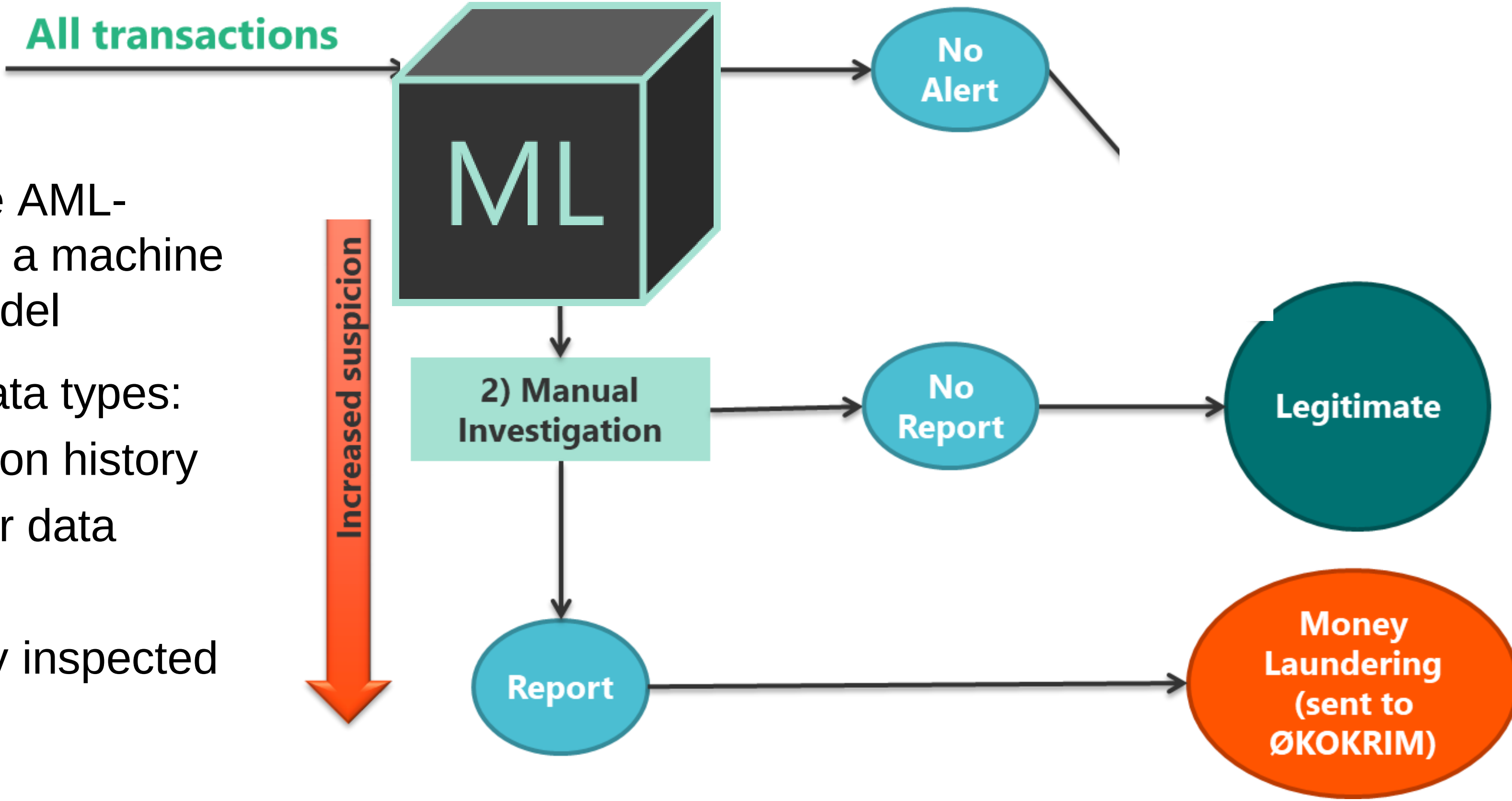
What we did

- Replace the AML-system with a machine learning model
- Available data types:
  - transaction history
  - customer data
  - alerts
  - manually inspected cases



What we did

More realistic setting!



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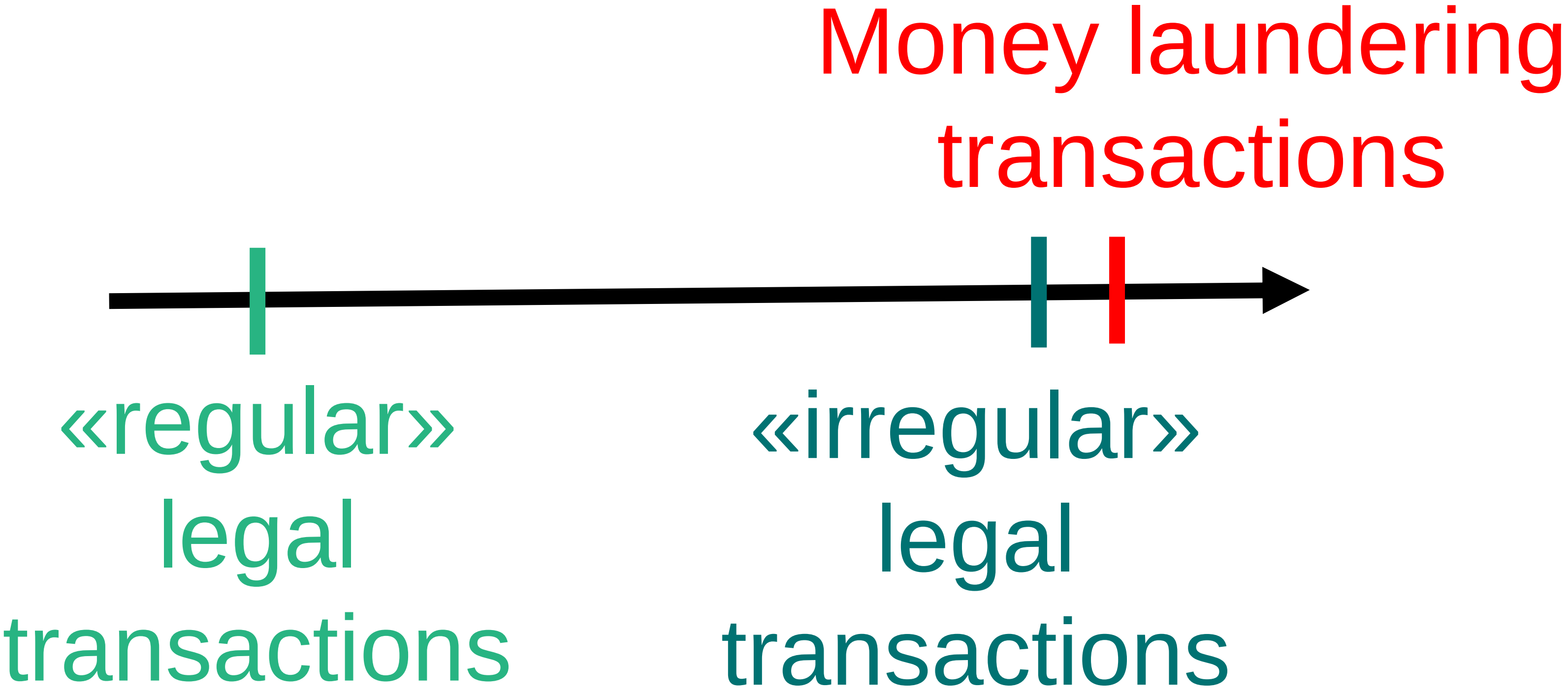
What makes this hard?

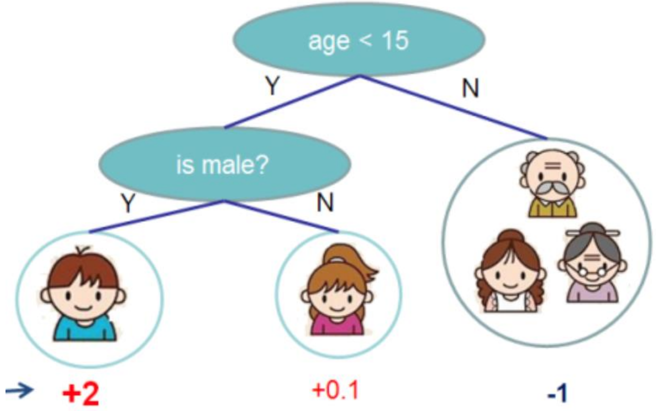


Modelling

- Binary response (Y): Transaction sent to Økokrim (Yes = 1, no = 0)
- Want to predict $P(Y = 1|\text{data related to present transaction})$

- State of the art: **Gradient boosting machines (GBM)**
- **XGBoost –** very efficient and flexible implementation of GBM based on tree models
  - **Requires tabular data input (features)**

dmlc XGBoost



Transforming raw data (feature engineering)

Input data types

- Specific transaction info
- Background info about sender/receiver
- Sender/receiver's transaction history
- Previously reported transactions from sender/receiver

Y	X1	X2	X3	X4	X5	X6
1	0,453406	0,992838	0,734389	0,159918	0,397515	0,949952
0	0,274	0,654207	0,169886	0,493841	0,407112	0,939789
0	0,741897	0,855005	0,585788	0,366456	0,365123	0,57955
1	0,488119	0,465754	0,716517	0,493048	0,855049	0,632114
0	0,134458	0,762057	0,848194	0,098779	0,872603	0,063026
0	0,531914	0,998817	0,808215	0,060721	0,716595	0,35374
0	0,341509	0,8398	0,637808	0,48304	0,279987	0,730286
0	0,530306	0,463271	0,338713	0,986781	0,925251	0,272484
1	0,864123	0,652763	0,689599	0,080937	0,990294	0,364736
0	0,106812	0,900351	0,450224	0,143815	0,593244	0,020764

1716 columns (features)

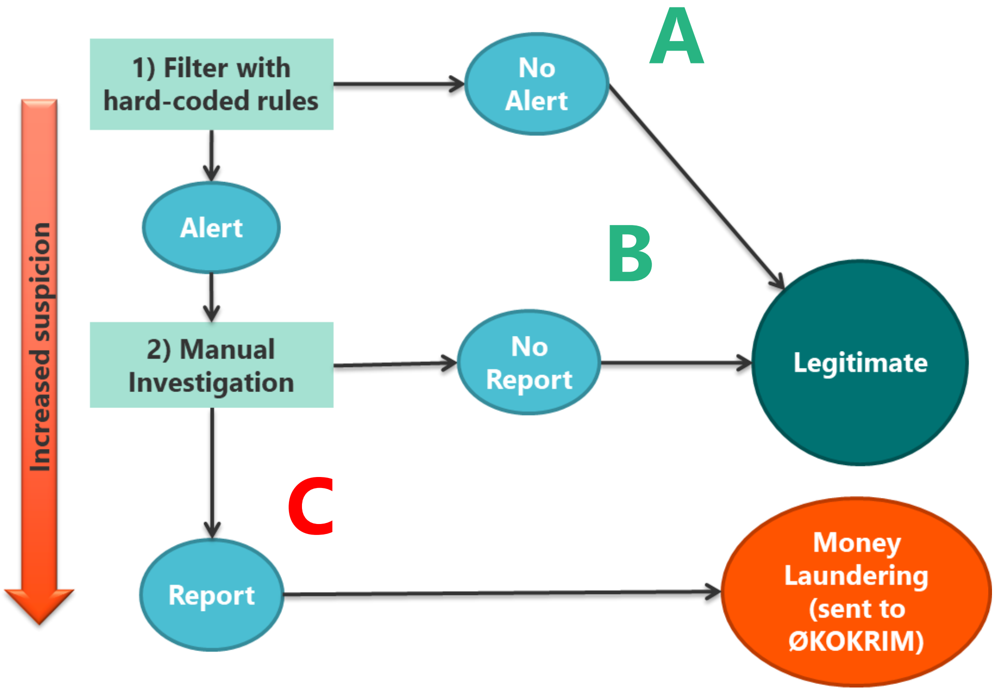
Data refinement

2 years of modellable transaction data

- All transactions leading to
  - A report (C)
  - An alert, but no report (B)
- A sample of normal transactions (A)

Data refinement

- We chose #A = #B
- Use only one transaction from each manual investigation (2)
- No transactions with same sender/receiver two consecutive days

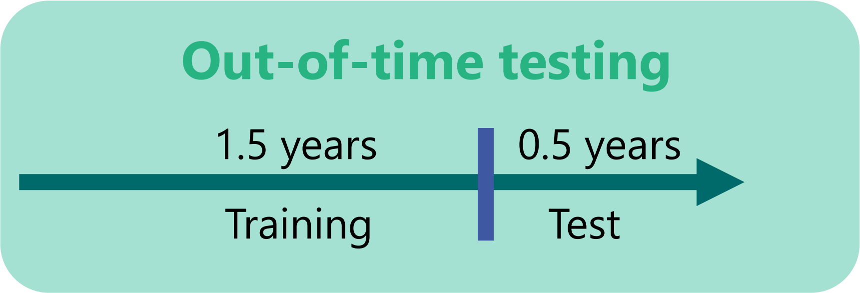


Training, testing and modelling

Modelling

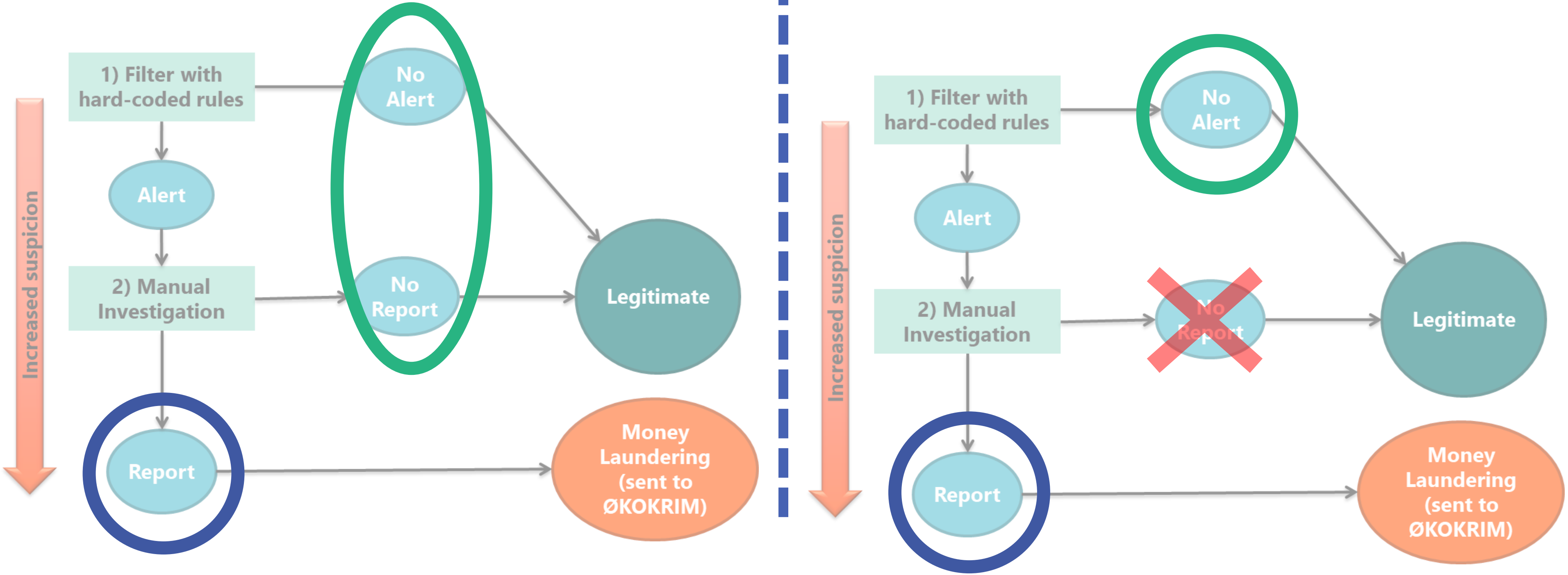
- 10-fold cross validation (CV)
- Stopping criterion (# boosting rounds): AUC
- Tuning: Random + iterative grid-search
- Model trained on GPU
- Final model used for prediction on test data:

$$\hat{f}(x_{\text{test}}) = \frac{1}{10}\sum_{i=1}^{10} \hat{f}_{CV,-i}(x_{\text{test}})$$



2 training scenarios

All data types | No unreported transactions



Evaluation metrics

Ranking:

AUC

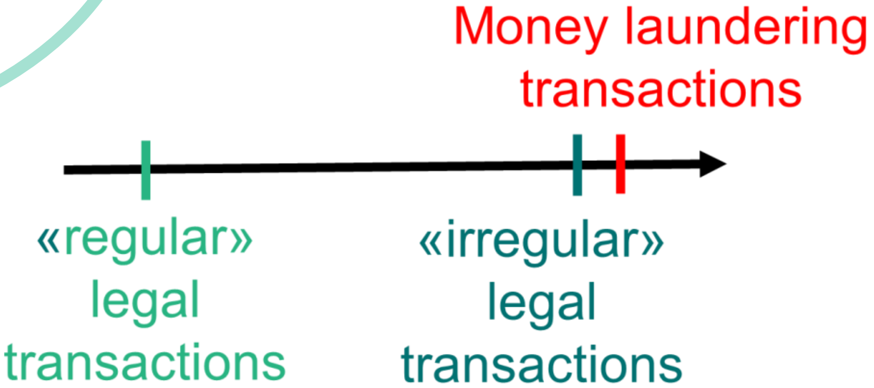
Probabilities:

Brier score

Comparing scenarios

	All data types	No unreported transactions
AUC	**0.907**	**0.852**
Brier	**0.025**	**0.340**

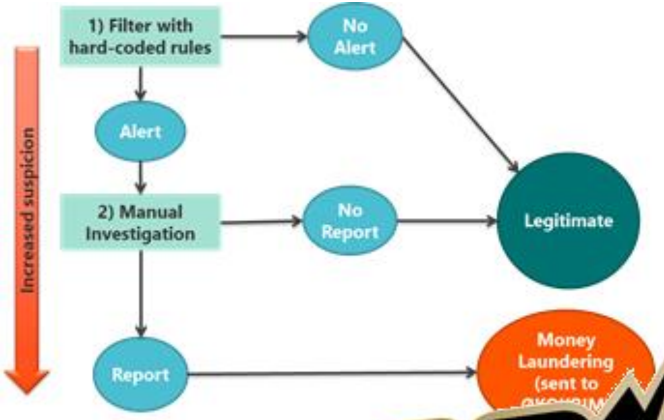
Much better!

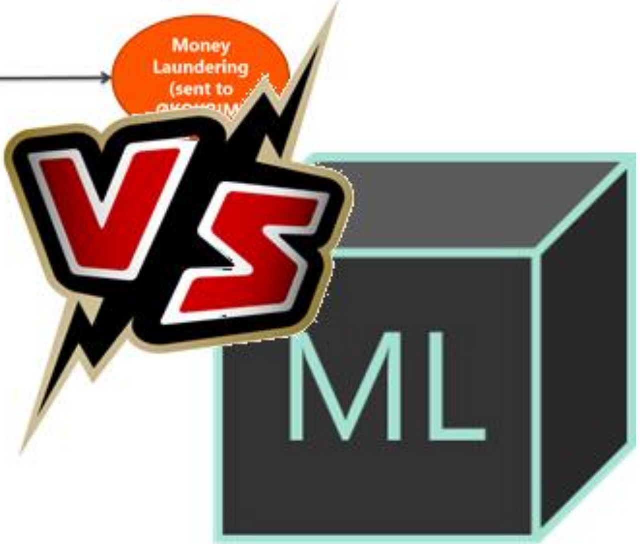


ML vs current AML system

- Hard to properly compare

- **PPP = Proportion of Positive Predictions:** Proportion of transactions that needs to be controlled to find 95% of the reported transactions





	ML (all data types)	Current system
PPP	31.5 %	48.9 %

Limitations

- We are not really using the **time-evolving transaction network**
  - **Who** are you sending/receiving money to/from
  - **When** are you sending/receiving
- Social/professional network information is not used
- Many variables – complicates putting the model into production
- The model only learns “known” what has already been reported

Further work

- To a greater extent utilize the transaction network
  - Methodology stemming form NLP (word2vec)
  - Training embeddings (numerical vectors) with neural networks to represent the transaction network for each customer

- Resources at DNB are working on utilizing customer's professional role network (Brønnøysundregisteret)

BigInsight