Detecting Money Laundering with Machine Learning

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Insurance seminar UiO 2020

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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
  - Buy (single premium) insurance policy (via straw person) with dirty money – surrender the policy

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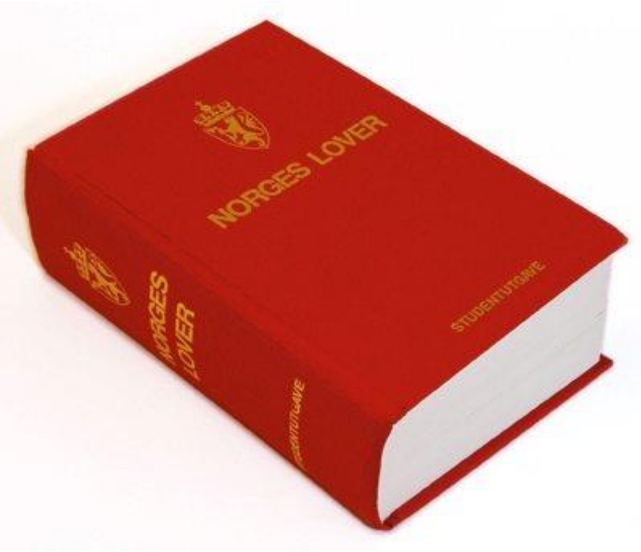

► All financial institutions are legally binded to report “suspicious transactions” to Økokrim

Why is AML important?


REUTERS

BUSINESS NEWS

MARCH 19, 2020 / 8:14 PM / 5 MONTHS AGO

Swedbank hit with record $386 million fine over Baltic money-laundering breaches

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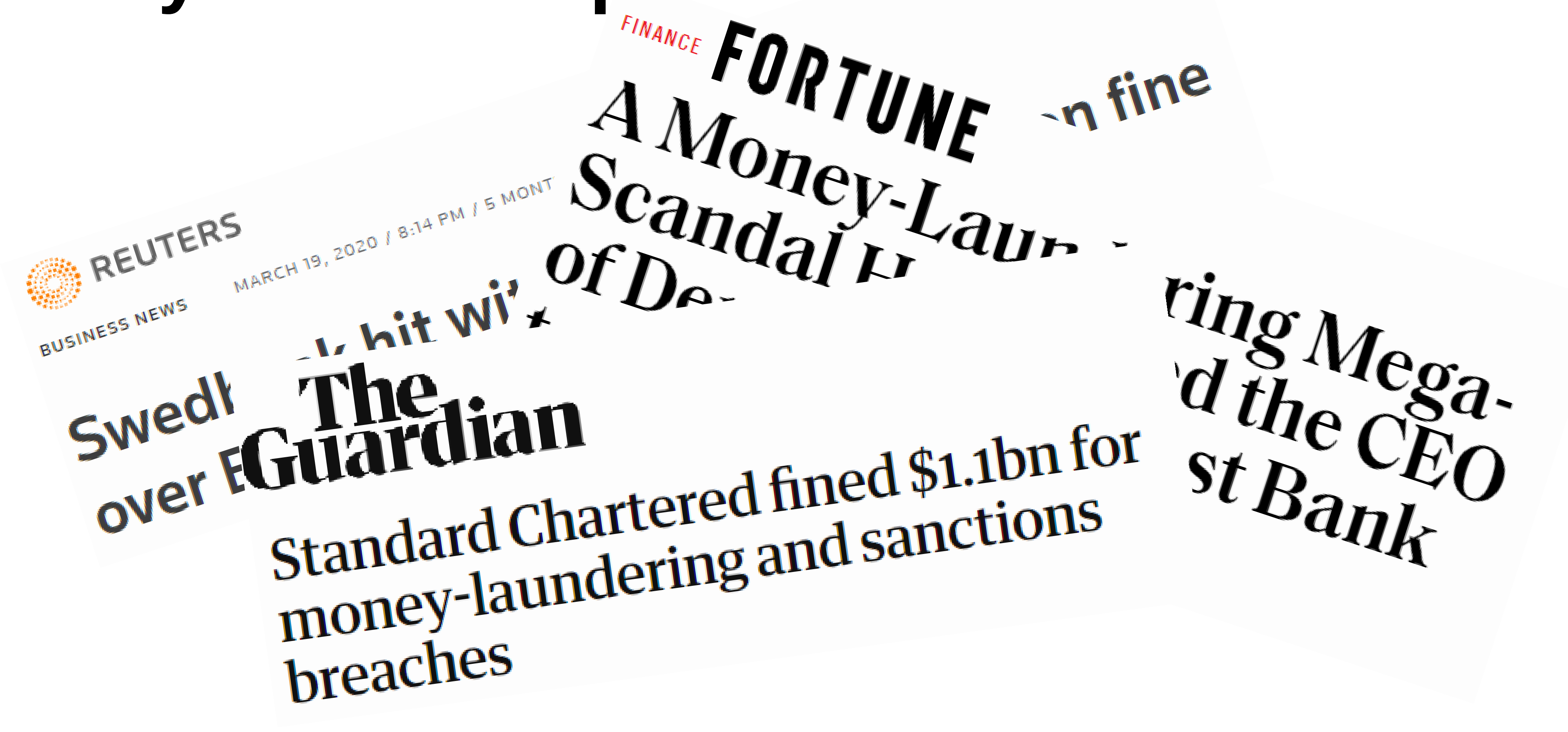
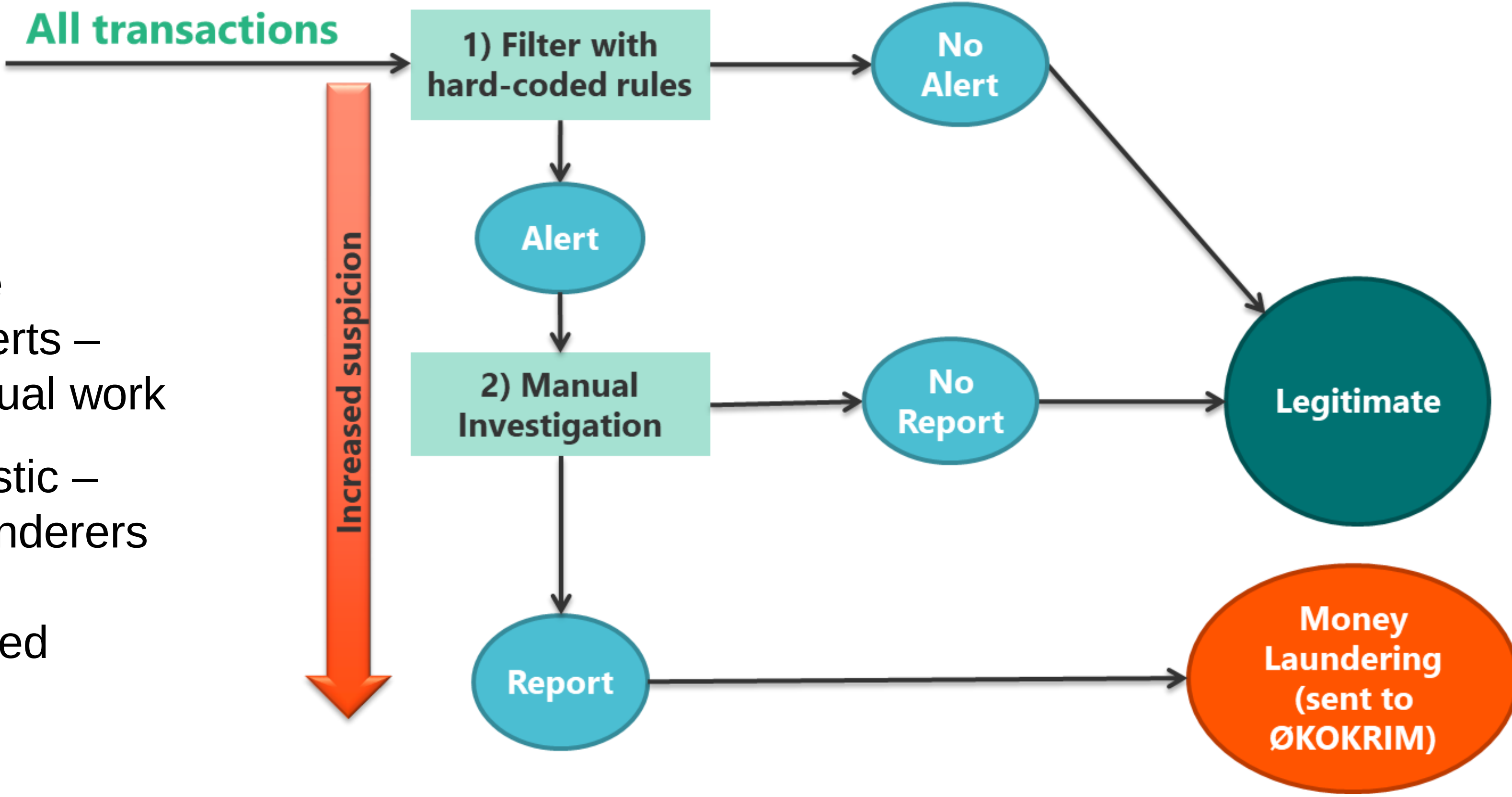


Why is AML important?

Current AML process at DNB

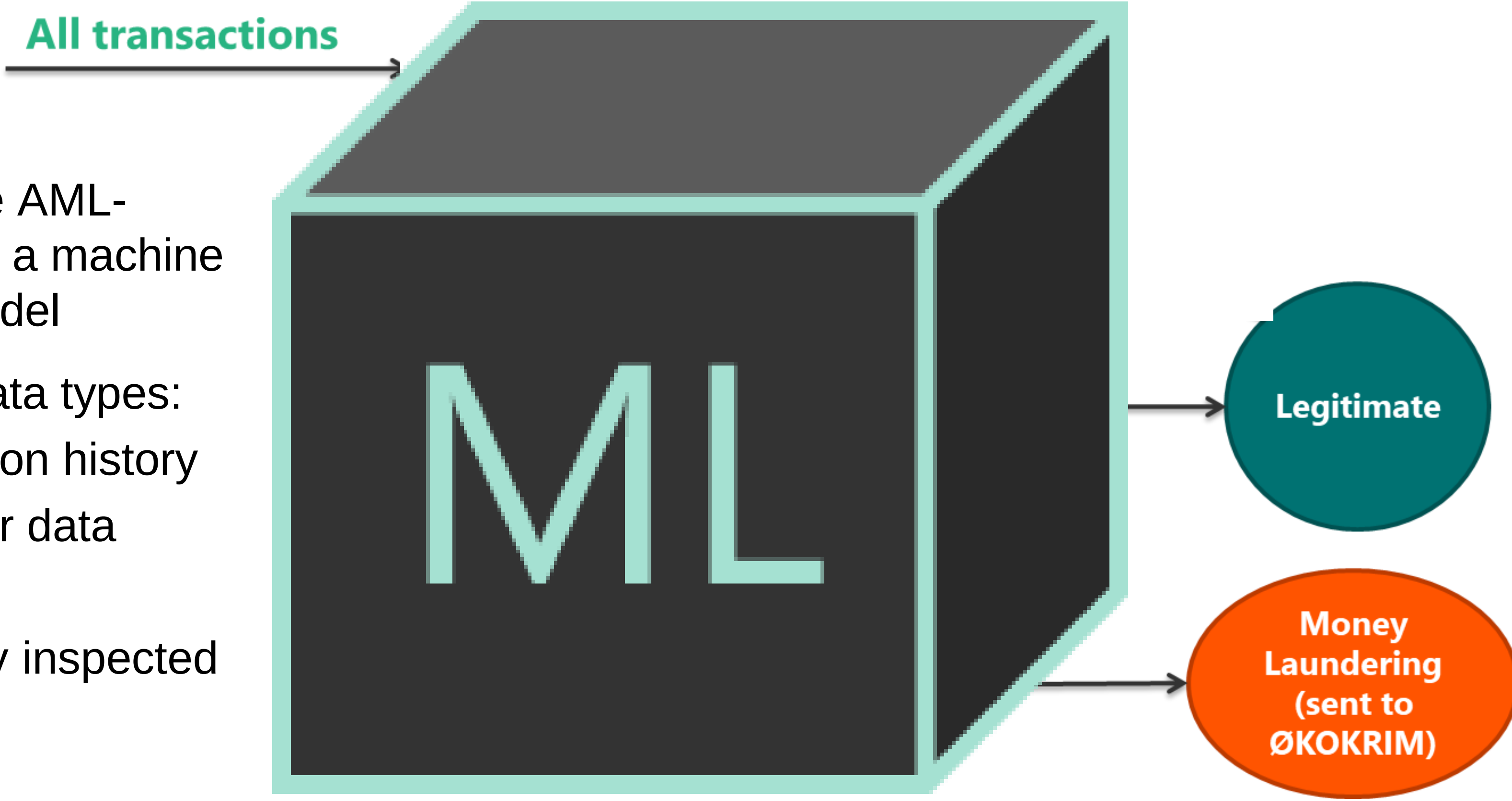


Weaknesses

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

What we have done

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



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More realistic setting!

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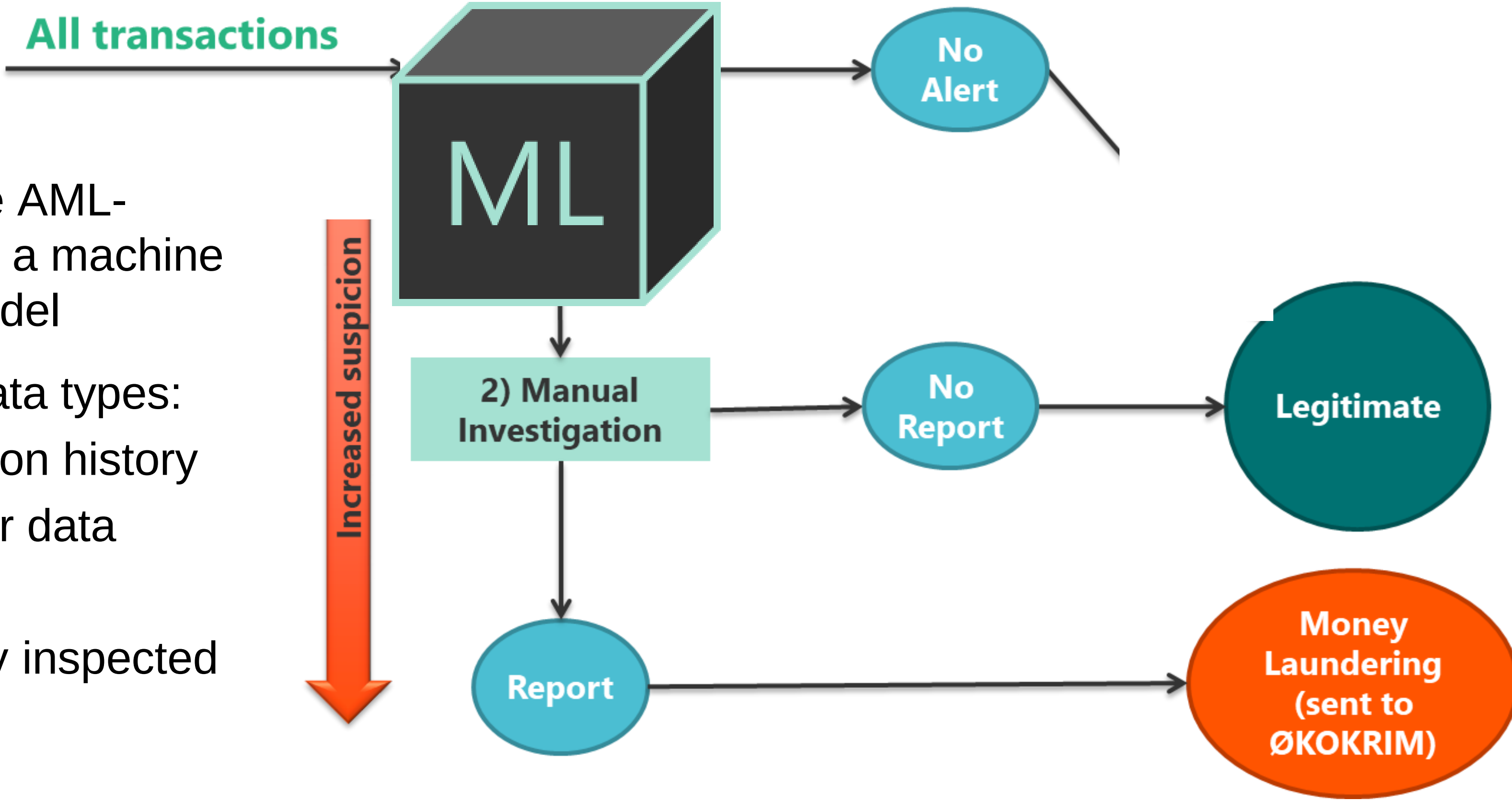
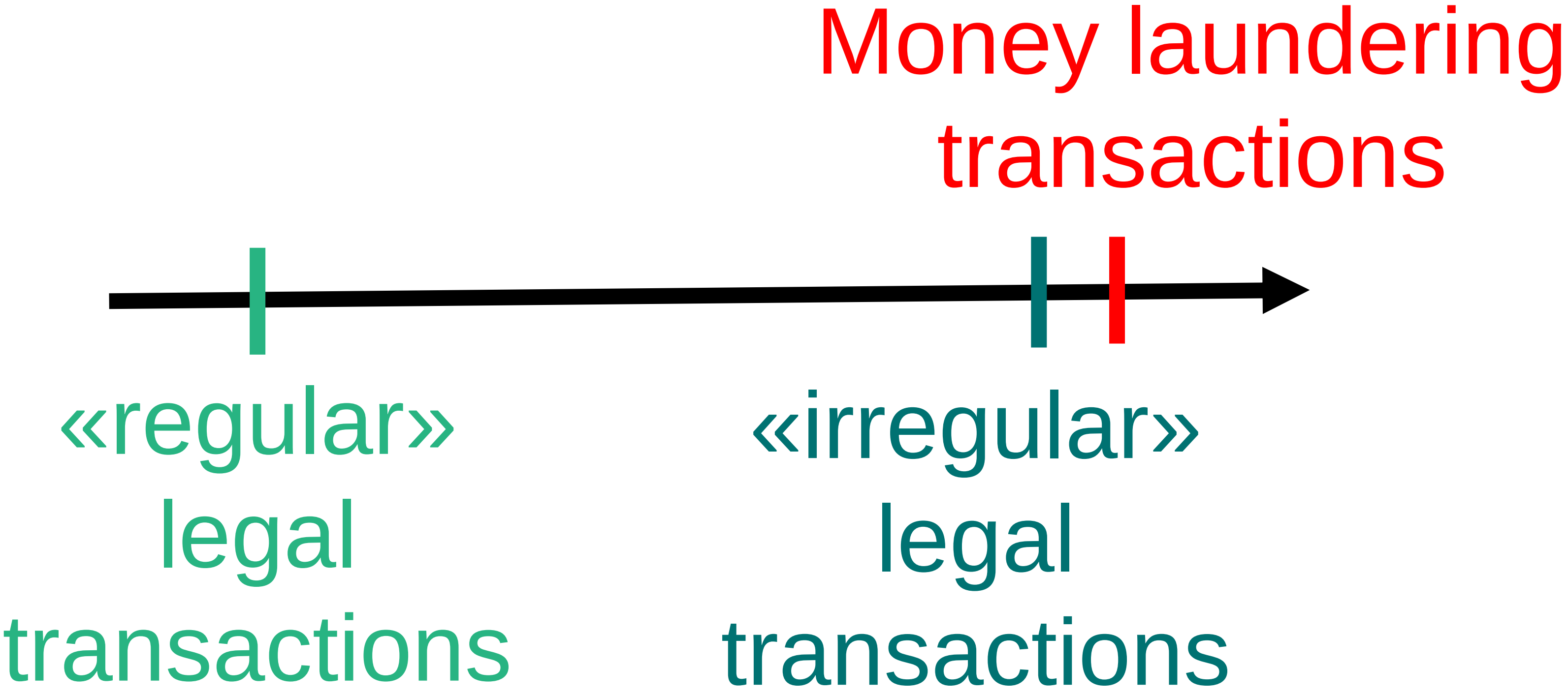


What makes this hard?

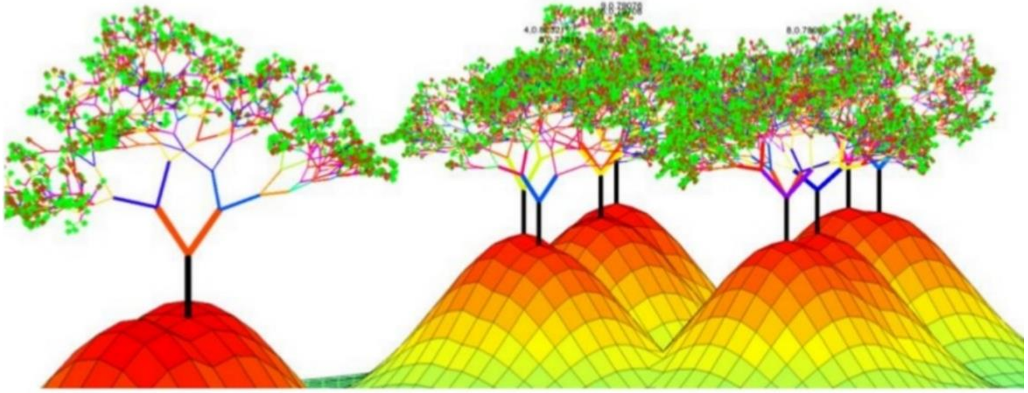


Modelling

- 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**

dmlc XGBoost



Tree models

Learn model $f(\boldsymbol{x}) \approx y$ using $\boldsymbol{x} = (x_1, \dots, x_p)$

- Conceptually very simple: Constructed as a series of IF-ELSE rules on x_i

$$f(\boldsymbol{x}) = \sum_{j=1}^{T} \theta_j \, 1_{\{\boldsymbol{x} \in R_j\}}$$

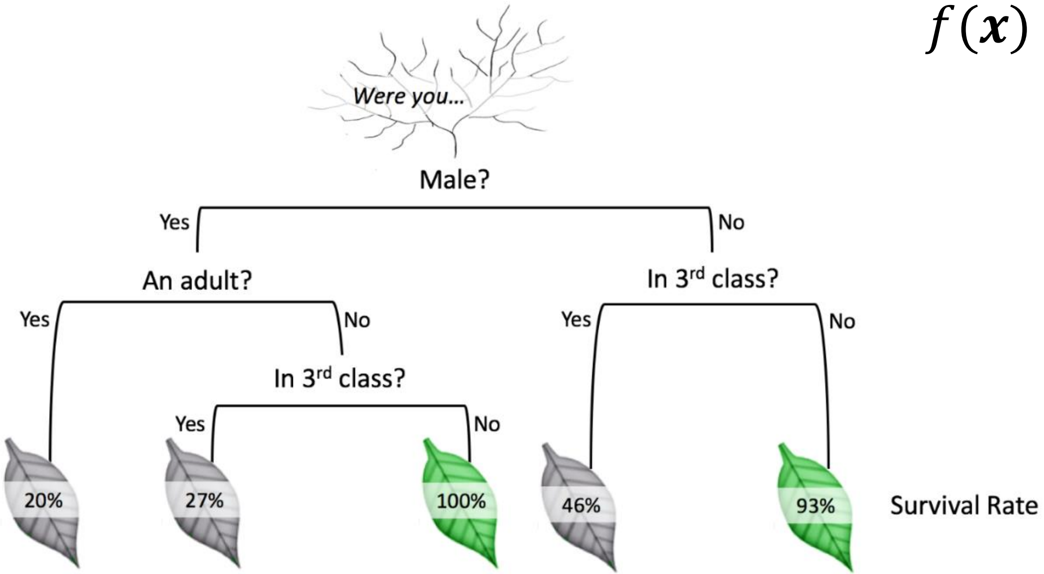
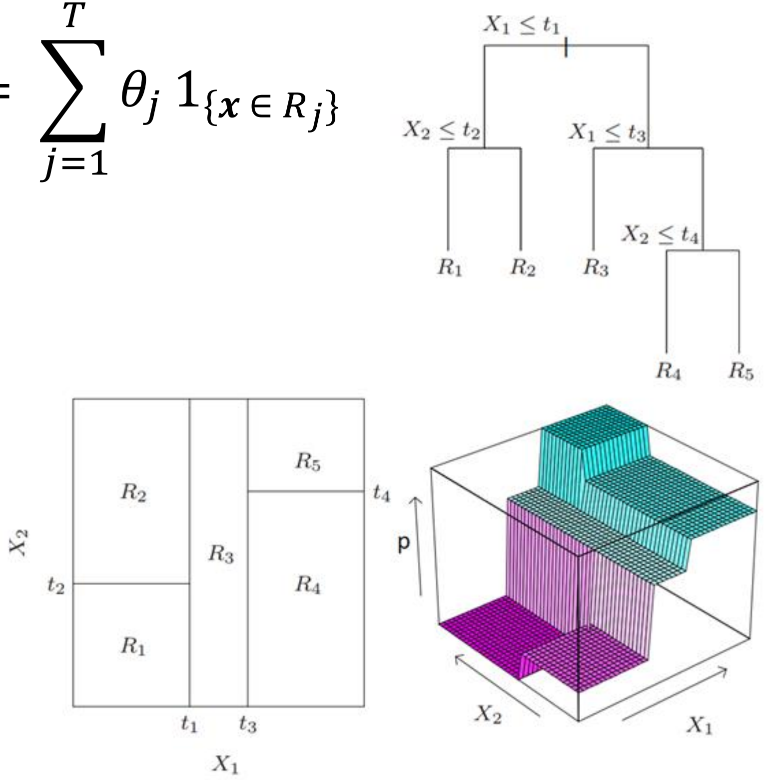


Illustration: Tree model for survival rate on Titanic



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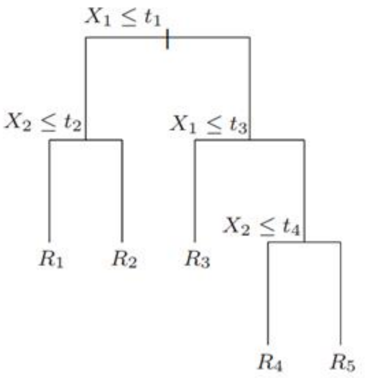
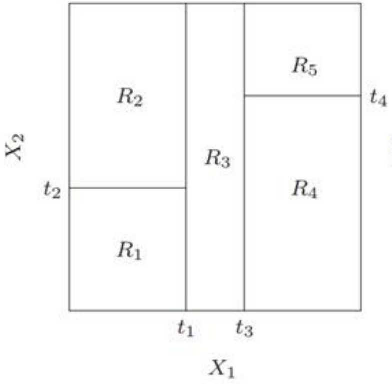
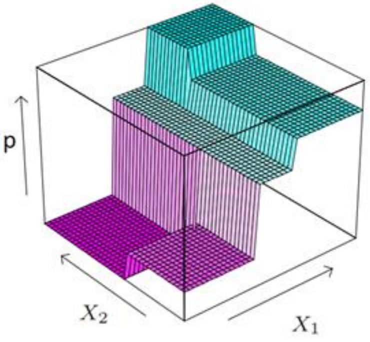


- Benefits:
  - Easy to train (greedy algorithm)
  - Direct modeling of non-linearities and interactions
  - Invariant under monotone transformations of $\boldsymbol{x}$
  - Naturally combines continuous and categorical features
- Drawbacks
  - High variance
  - Limited predictive power





Boosting

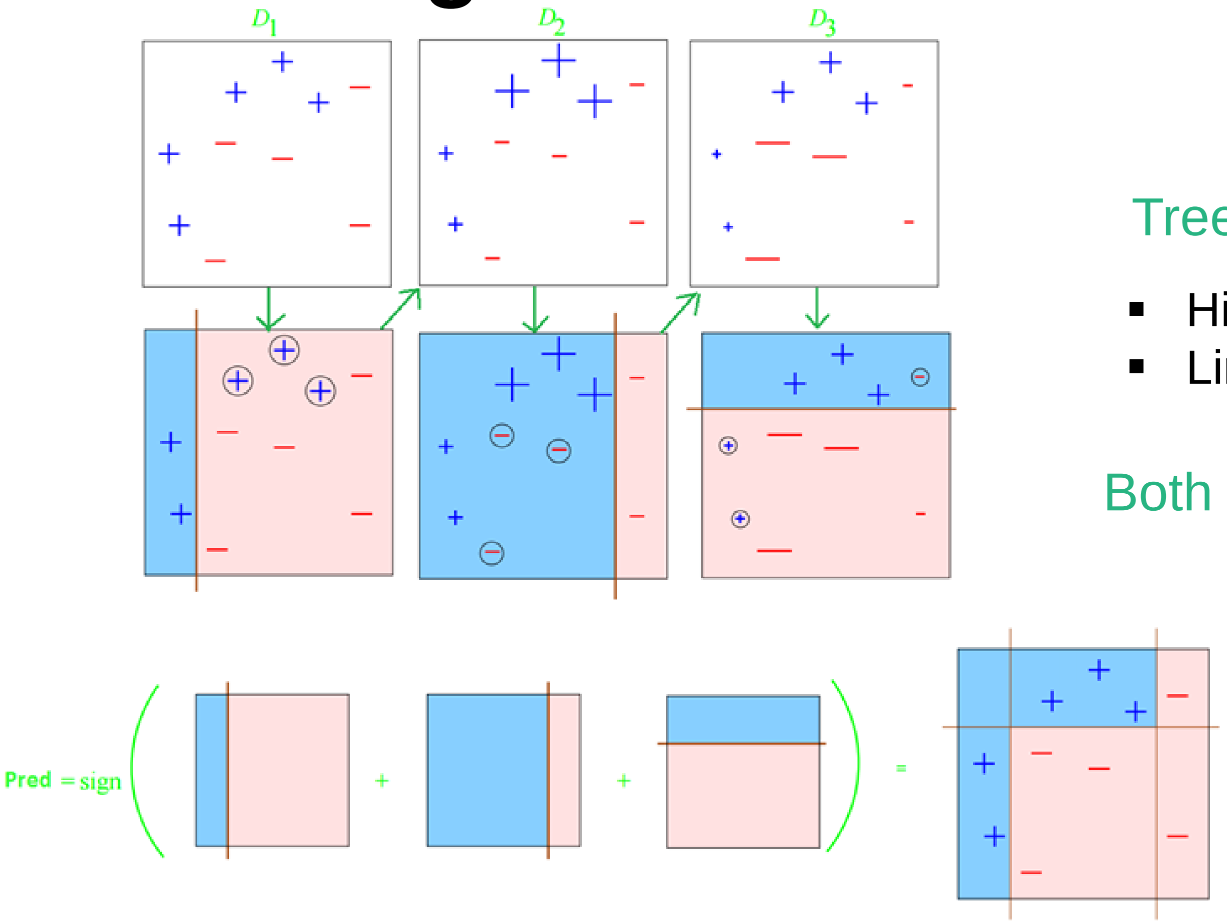
- Given some loss function $L(y, \cdot)$, iteratively fit simple models $f_m(\boldsymbol{x})$ (weak learners) trying to correct «errors» of previous models:

$$f_m(\boldsymbol{x}) = \underset{h \in \Phi}{\operatorname{argmin}}\, s_h(x), \qquad s_h(x) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, f^{(m-1)}(x_i) + h(x_i))$$

and sum them into a strong learner

$$f^{(M)}(\boldsymbol{x}) = \sum_{m=1}^{M} f_m(\boldsymbol{x})$$

Boosting illustration

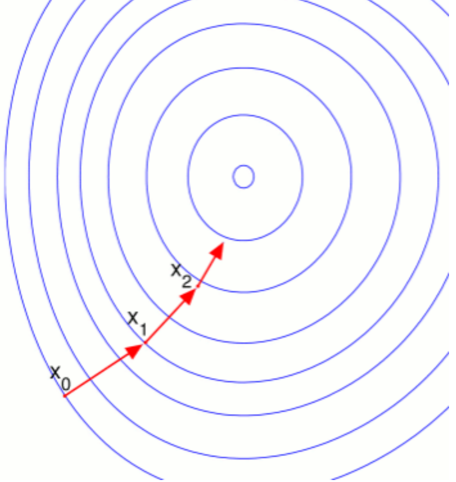


Tree model drawbacks

- High variance
- Limited predictive power

Both fixed using boosting!

XGBoost and gradient boosting



- Generally hard to solve

$$\operatorname*{argmin}_{h \in \Phi} s_h(x), \qquad s_h(x) = \frac{1}{n}\sum_{i=1}^{n} L(y_i, f^{(m-1)}(x_i) + h(x_i))$$

- Gradient boosting: Take a (functional) gradient descent-step towards the minimum of $s_h(x)$ instead of solving it globally

- XGBoost ++ uses a variant of Newton's method, also involving the hessian (but typically still calls it Gradient boosting)

Transforming raw data (feature engineering)

- XGBoost requires numeric tabular data as input!

Raw input data

- 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)

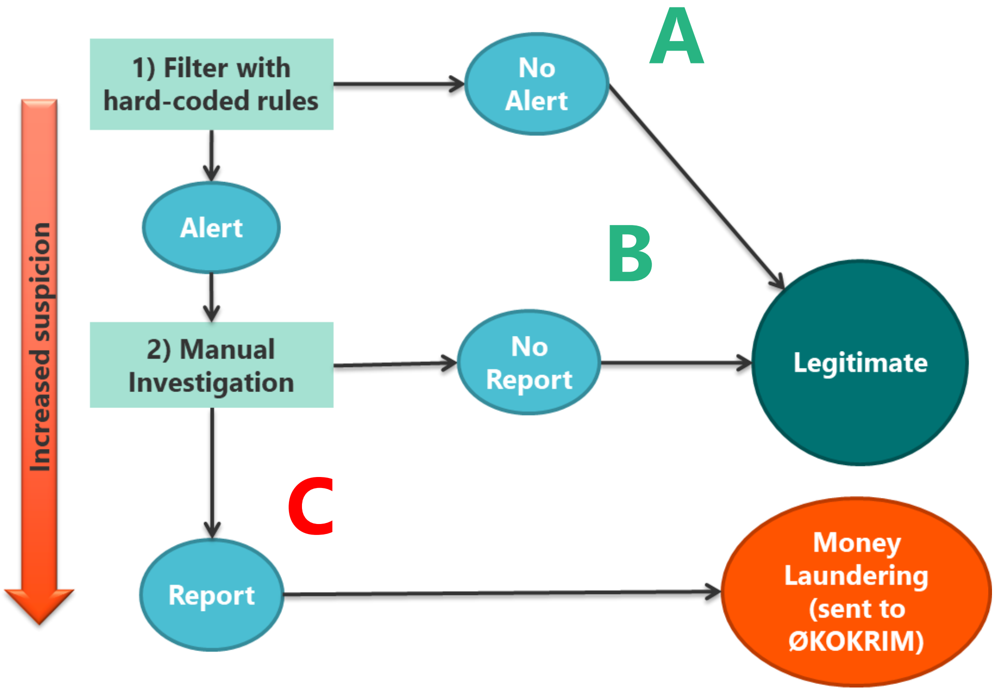
Data refinement

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

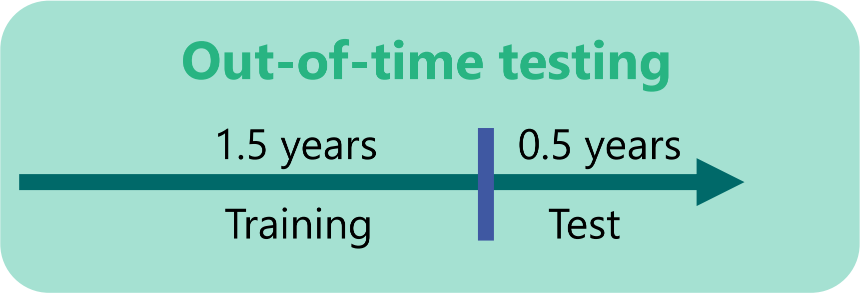


Training, testing and modelling

Modelling

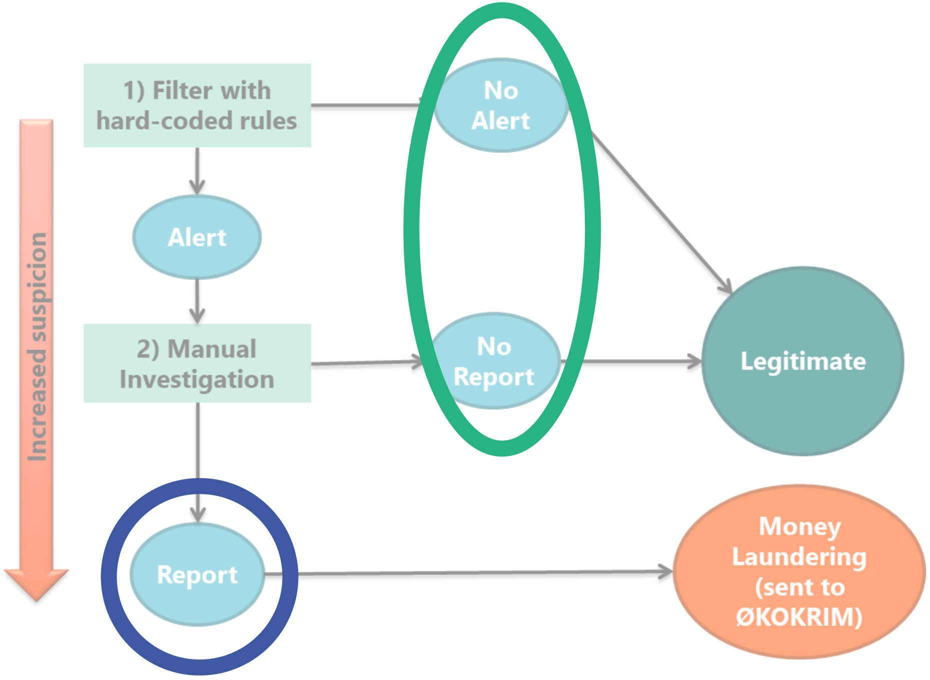
- 10-fold cross validation (CV)
- Stopping criterion (# boosting rounds): AUC
- Tuning: Random + iterative grid-search
- Model trained on GPU
- Final model used for prediction on test data:

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

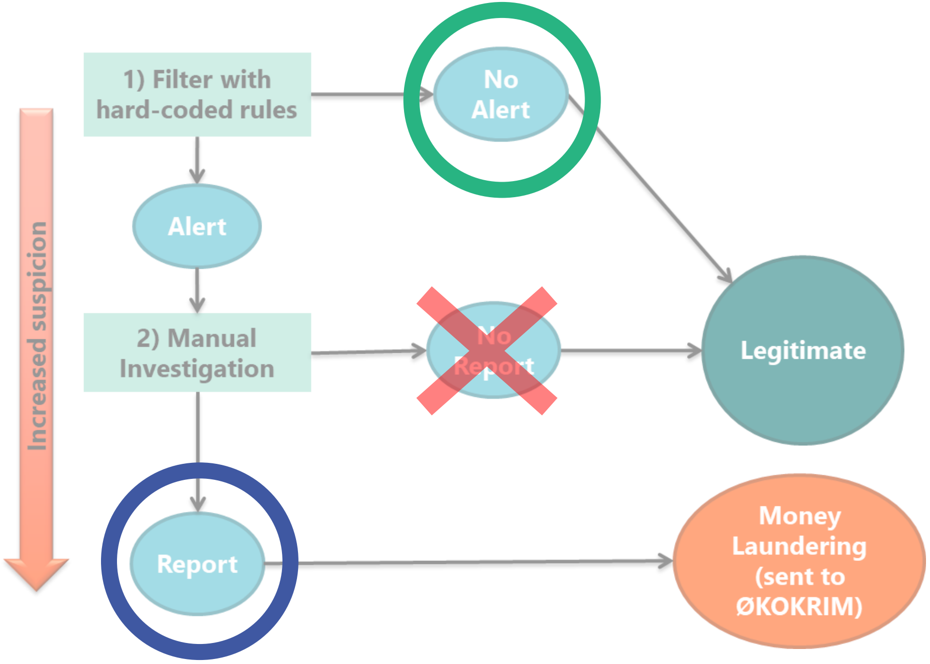


2 training scenarios

All data types

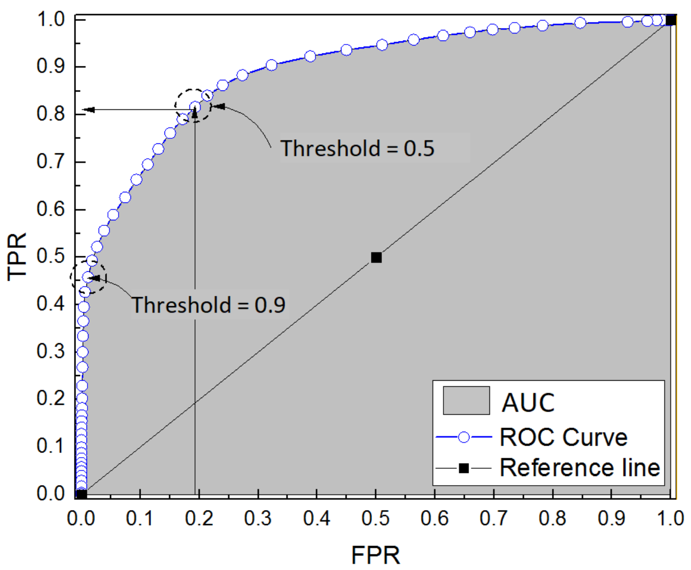


No unreported transactions



Evaluation metrics

Ranking:
AUC



Probabilities:
Brier score

$$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} (y_i - \hat{p}_i)^2$$

Comparing scenarios

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

Much better!

Money laundering transactions

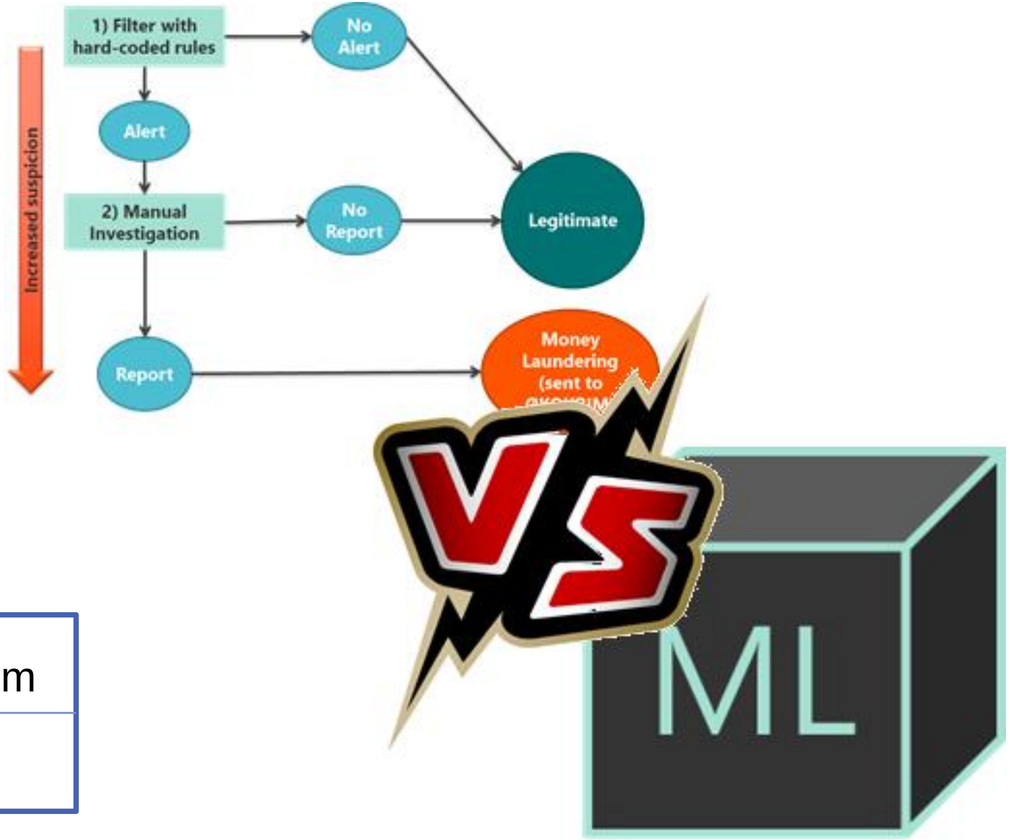
«regular» legal transactions

«irregular» legal transactions

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 %

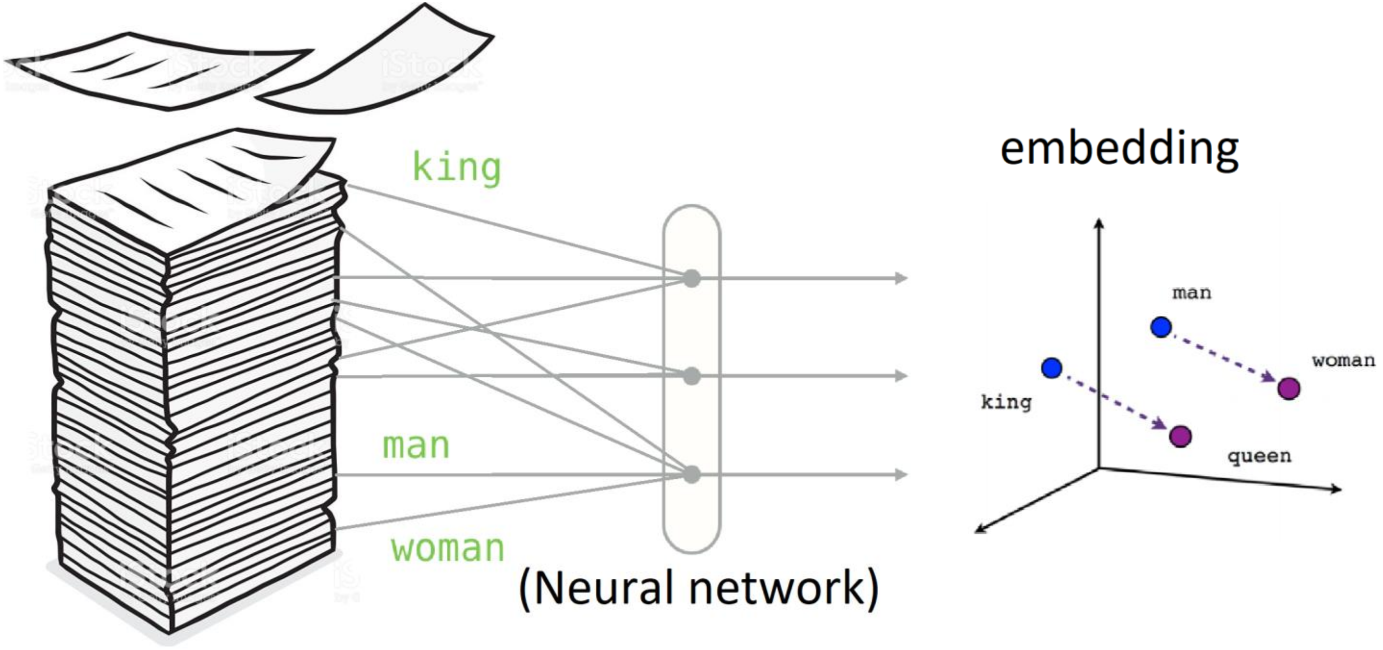
Limitations

- 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 what has already been reported

Current work: Utilize the transaction <u>network</u>

- Borrowing strength from NLP (Natural Language Processing)

word2vec



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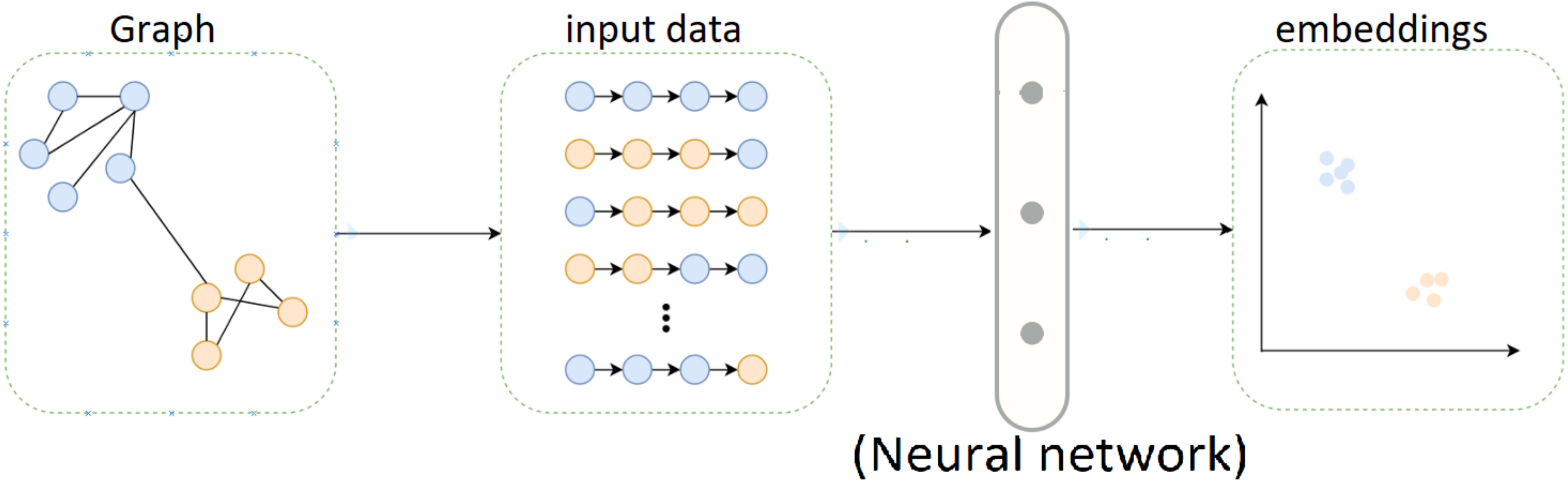

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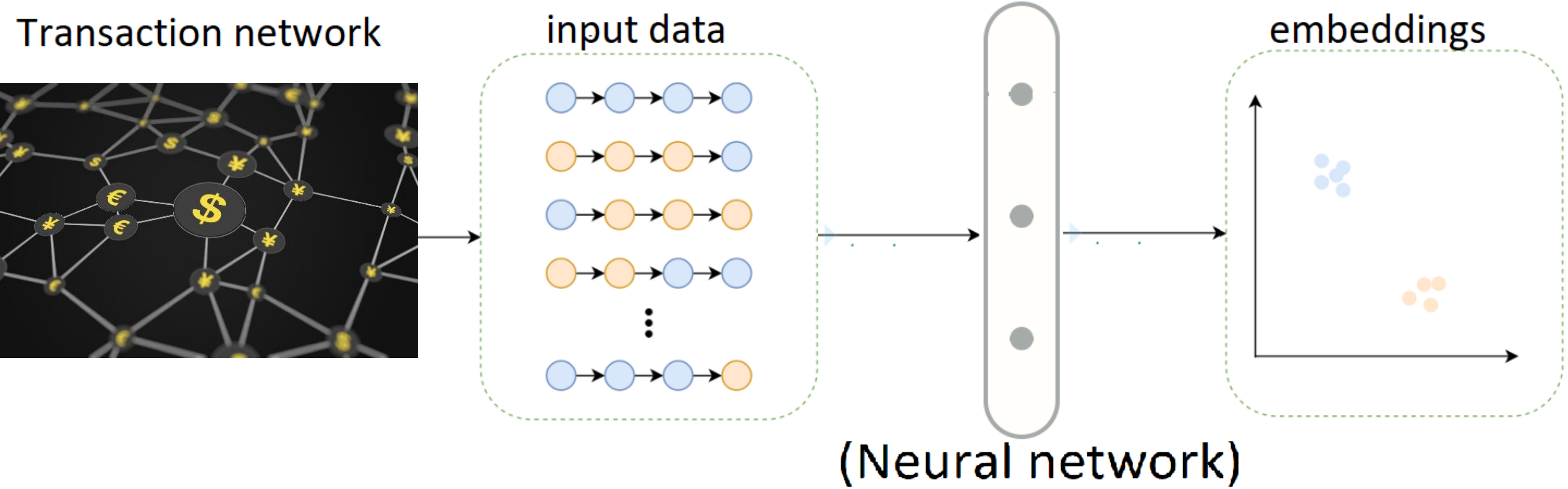

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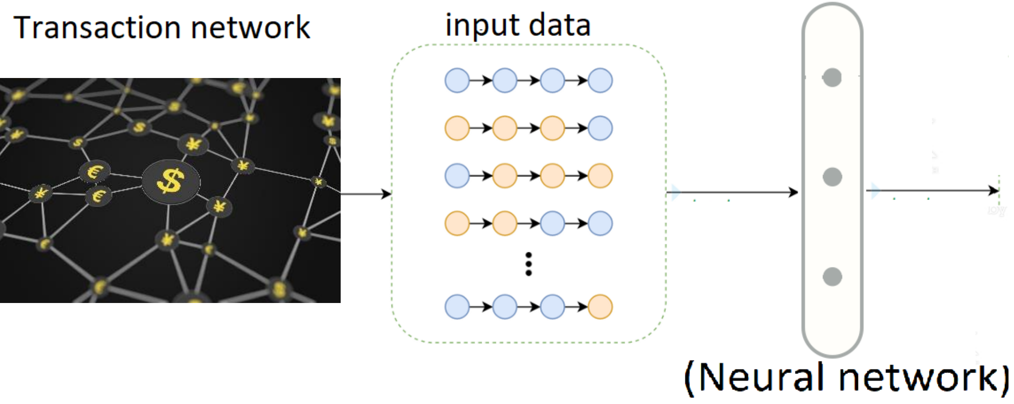

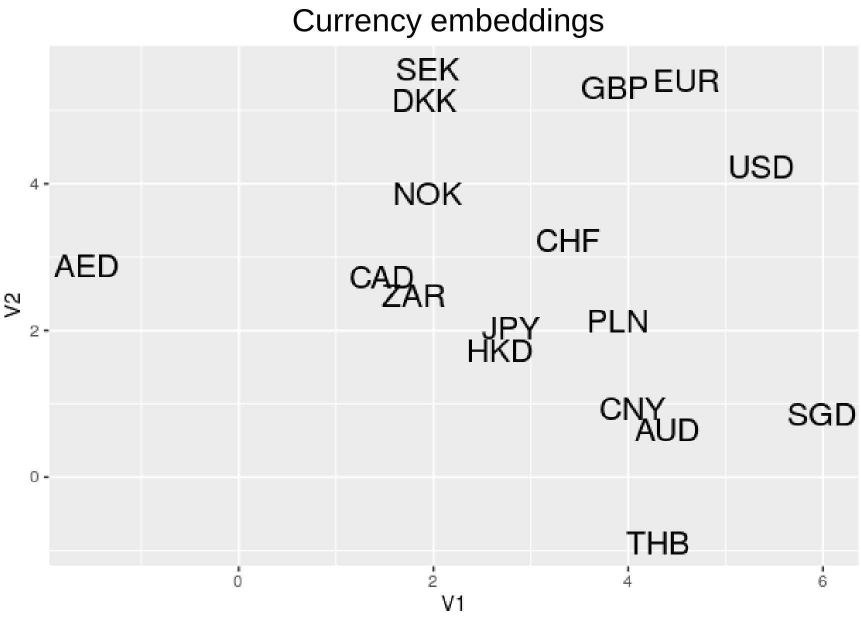

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