A Prototype for Credit Card Fraud Management

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http://speedd-project.eu/
Credit Card Fraud Management

Input:
- Credit card transactions from all over the world.

Output:
- Cloned card — a credit card is being used simultaneously in different countries.
- New high use — the card is being frequently used in merchants or countries never used before.
- Potential batch fraud — many transactions from multiple cards in the same point-of-sale terminal in high amounts.
Credit Card Fraud Management: Challenges

- Fraud must be detected within 25 milliseconds.
Credit Card Fraud Management: Challenges

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- **Fraudulent transactions: <0.2%** of the total number of transactions.
Credit Card Fraud Management: Challenges

- Fraud must be detected within 25 milliseconds.
- Fraudulent transactions: <0.2% of the total number of transactions.
- Fraud is constantly evolving.
Credit Card Fraud Management: Challenges

- Fraud must be detected within 25 milliseconds.
- **Fraudulent transactions:** <0.2% of the total number of transactions.
- Fraud is **constantly evolving**.
- Erroneous transactions, missing fields.
Credit Card Fraud Management: SPEEDD Prototype

- Automated, online fraud pattern construction.
- Fraud detection.
- User Interface.
Credit Card Fraud Management: SPEEDD Prototype

▶ Automated, online fraud pattern construction.
▶ Fraud detection (DEBS 2015).
▶ User Interface.
Automated Pattern Construction: Inductive Logic Programming (ILP)

Input:
- Positive and negative examples.
- Background knowledge.
- Language bias.

Output:
- A logical theory that entails as many positive and as few negative examples as possible.
Example Fraud Patterns

fraud(CardId, T2) ←
  transaction(CardId, massive_amount, T2),
  transaction(CardId, tiny_amount, T1),
  before(T1, T2),
  within(T1, T2, 1).

fraud(CardId, T2) ←
  transactionsAtLeast(CardId, 6),
  within(T1, T2, 7),
  before(T1, T2).
Background Knowledge & Language Bias

Learnt Hypothesis $H_t$:

\[
\begin{align*}
\text{fraud}(\text{CardId}, T_2) & \leftarrow \\
& \text{trans}(\text{Card, massive_amount, } T_2), \\
& \text{trans}(\text{Card, tiny_amount, } T_1), \\
& \text{before}(T_1, T_2), \\
& \text{within}(T_1, T_2, 2).
\end{align*}
\]

Data Stream/Training Examples

Training example $I_t$

\[
\begin{align*}
\text{trans}(1500653, 420.0, \text{d5b9ab0b181}, \text{200902, fraud}), \\
\text{trans}(1500654, 0, 35, \text{d5b9ab0b181}, \text{200902, fraud}), \\
\text{trans}(1500655, 154.5, \text{d5b9ab0b181}, \text{200902, fraud}), \\
\text{trans}(1500656, 180.4, \text{d5b9ab0b181}, \text{200902, fraud}), \\
\text{trans}(1500657, 2.34, \text{d5b9ab0b181}, \text{200902, fraud})
\end{align*}
\]

Training example $I_{t'}$

\[
\begin{align*}
\text{trans}(1856635, 420.0, \text{3348af85}, \text{200902, nofraud}), \\
\text{trans}(1856636, 0, 35, \text{3348af85}, \text{200902, nofraud}), \\
\text{trans}(1856637, 154.5, \text{3348af85}, \text{200902, nofraud}), \\
\text{trans}(1856638, 180.4, \text{3348af85}, \text{200902, nofraud}), \\
\text{trans}(1856639, 2.34, \text{3348af85}, \text{200902, nofraud})
\end{align*}
\]
Online Learning: The OLED System

Background Knowledge & Language Bias

Learnt Hypothesis $H_t$: $\text{fraud}(\text{CardId}, T_2)$ \leftarrow $\text{trans}(\text{Card}, \text{massive_amount}, T_2)$, $\text{trans}(\text{Card}, \text{tiny_amount}, T_1)$, $\text{before}(T_1, T_2)$, $\text{within}(T_1, T_2, 2)$.

OLED

Theory Expansion

Data Stream/Training Examples

Training example $I_t$

$\text{trans}(1500653, 420.0, d5b9ab0b181, 200902, \text{fraud})$, $\text{trans}(1500654, 0, 35, d5b9ab0b181, 200902, \text{fraud})$, $\text{trans}(1500655, 154.5, d5b9ab0b181, 200902, \text{fraud})$, $\text{trans}(1500656, 180.4, d5b9ab0b181, 200902, \text{fraud})$, $\text{trans}(1500657, 2.34, d5b9ab0b181, 200902, \text{fraud})$.

Training example $I_t'$

$\text{trans}(1856635, 420.0, 3348af85, 200902, \text{nofraud})$, $\text{trans}(1856636, 0, 35, 3348af85, 200902, \text{nofraud})$, $\text{trans}(1856637, 154.5, 3348af85, 200902, \text{nofraud})$, $\text{trans}(1856638, 180.4, 3348af85, 200902, \text{nofraud})$, $\text{trans}(1856639, 2.34, 3348af85, 200902, \text{nofraud})$. 

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Online Learning: The OLED System

Background Knowledge & Language Bias

Learnt Hypothesis $H_t$:

$fraud(CardId, T_2) \leftarrow$

$trans(Card, massive\_amount, T_2),$

$trans(Card, tiny\_amount, T_1),$

$before(T_1, T_2),$

$within(T_1, T_2, 2).$

Training example $I_t$

$trans(1500653, 420.0, d5b9ab0b181, 200902, fraud),$

$trans(1500654, 0, 35, d5b9ab0b181, 200902, fraud),$

$trans(1500655, 154.5, d5b9ab0b181, 200902, fraud),$

$trans(1500656, 180.4, d5b9ab0b181, 200902, fraud),$

$trans(1500657, 2.34, d5b9ab0b181, 200902, fraud).$

Training example $I_t'$

$trans(1856635, 420.0, 3348af85, 200902, nofraud),$

$trans(1856636, 0, 35, 3348af85, 200902, nofraud),$

$trans(1856637, 154.5, 3348af85, 200902, nofraud),$

$trans(1856638, 180.4, 3348af85, 200902, nofraud),$

$trans(1856639, 2.34, 3348af85, 200902, nofraud).$

Data Stream/Training Examples

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Online Learning: The OLED System

Background Knowledge & Language Bias

Learnt Hypothesis $H_t$: 
\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \\
\text{trans}((\text{Card}, \text{massive_amount}, T_2)), \\
\text{trans}((\text{Card}, \text{tiny_amount}, T_1)), \\
\text{before}(T_1, T_2), \\
\text{within}(T_1, T_2, 2).
\]

OLED

Theory Expansion

Rule Expansion

Rule Evaluation

Data Stream/Training Examples

Training example $I_t$
\[
\begin{align*}
\text{trans}(1500653, 420.0, d5b9ab0b181, 200902, \text{fraud}), \\
\text{trans}(1500654, 0, 35, d5b9ab0b181, 200902, \text{fraud}), \\
\text{trans}(1500655, 154.5, d5b9ab0b181, 200902, \text{fraud}), \\
\text{trans}(1500656, 180.4, d5b9ab0b181, 200902, \text{fraud}), \\
\text{trans}(1500657, 2.34, d5b9ab0b181, 200902, \text{fraud})
\end{align*}
\]

Training example $I_{t'}$
\[
\begin{align*}
\text{trans}(1856635, 420.0, 3348af85, 200902, \text{nofraud}), \\
\text{trans}(1856636, 0, 35, 3348af85, 200902, \text{nofraud}), \\
\text{trans}(1856637, 154.5, 3348af85, 200902, \text{nofraud}), \\
\text{trans}(1856638, 180.4, 3348af85, 200902, \text{nofraud}), \\
\text{trans}(1856639, 2.34, 3348af85, 200902, \text{nofraud})
\end{align*}
\]
Online Learning: The OLED System

Learnt Hypothesis $\mathcal{H}_t$:

- $\text{fraud}(\text{CardId}, T_2) \leftarrow$
  - $\text{trans}(\text{Card}, \text{massive\_amount}, T_2)$,
  - $\text{trans}(\text{Card}, \text{tiny\_amount}, T_1)$,
  - $\text{before}(T_1, T_2)$,
  - $\text{within}(T_1, T_2, 2)$.

- $\text{fraud}(\text{CardId}, T_2) \leftarrow$
  - $\text{transAtLeast}(\text{Card}, 6)$,
  - $\text{within}(T_1, T_2, 7)$,
  - $\text{before}(T_1, T_2)$.

Background Knowledge & Language Bias

Data Stream/Training Examples

Training example $I_t$

- $\text{trans}(1500653, 420.0, \text{d5b9ab0b181}, 200902, \text{fraud})$,
- $\text{trans}(1500654, 0, 35, \text{d5b9ab0b181}, 200902, \text{fraud})$,
- $\text{trans}(1500655, 154.5, \text{d5b9ab0b181}, 200902, \text{fraud})$,
- $\text{trans}(1500656, 180.4, \text{d5b9ab0b181}, 200902, \text{fraud})$,
- $\text{trans}(1500657, 2.34, \text{d5b9ab0b181}, 200902, \text{fraud})$.

Training example $I'_t$

- $\text{trans}(1856635, 420.0, \text{3348af85}, 200902, \text{nofraud})$,
- $\text{trans}(1856636, 0, 35, \text{3348af85}, 200902, \text{nofraud})$,
- $\text{trans}(1856637, 154.5, \text{3348af85}, 200902, \text{nofraud})$,
- $\text{trans}(1856638, 180.4, \text{3348af85}, 200902, \text{nofraud})$,
- $\text{trans}(1856639, 2.34, \text{3348af85}, 200902, \text{nofraud})$.
Candidate Rules

$R_1$: 0.345

$R_2$: 0.232

$R_3$: 0.145

$R_4$: 0.612

$R_5$: 0.325

Training stream

Find the best candidate across the stream

With confidence $1 - \delta$, we have

$\bar{X} - \epsilon \leq \hat{X} \leq \bar{X} + \epsilon$,

where

$\epsilon = \sqrt{\ln \left(\frac{1}{\delta}\right)}$.

Then

$\bar{X} - \epsilon > 0 \Rightarrow \hat{X} > 0 \Rightarrow$ Best Rule is indeed the best rule, with probability $1 - \delta$. 

As examples stream in...

Monitor $\bar{X} = \text{score}_{\text{BestRule}} - \text{score}_{\text{SecondBestRule}}$

Continue until the number $N$ of examples makes $\bar{X} > \epsilon = \sqrt{\ln \left(\frac{1}{\delta}\right)}$. Then $\bar{X} - \epsilon > 0 \Rightarrow \hat{X} > 0 \Rightarrow$ Best Rule is indeed the best rule, with probability $1 - \delta$. 

Online Rule Learning
Online Rule Learning

Candidate Rules

$R_1: 0.345$

$R_2: 0.232$
$R_3: 0.145$

$R_4: 0.612$
$R_5: 0.325$

As examples stream in...

Monitor $\bar{X} = \overline{\text{score}}_{\text{BestRule}} - \overline{\text{score}}_{\text{SecondBestRule}}$

Find the best candidate across the stream

Training stream
Online Rule Learning

Candidate Rules

$R_1: 0.345$

$R_2: 0.232$

$R_3: 0.145$

$R_4: 0.612$

$R_5: 0.325$

Training stream

Find the best candidate across the stream

With confidence $1 - \delta$, we have

$\bar{X} - \epsilon \leq \hat{X} \leq \bar{X} + \epsilon$, where $\epsilon = \sqrt{\frac{\ln(1/\delta)}{2N}}$

As examples stream in...

Monitor $\bar{X} = \text{score}_{\text{BestRule}} - \text{score}_{\text{SecondBestRule}}$
Online Rule Learning

Candidate Rules

$R_1: 0.345$
$R_2: 0.232$
$R_3: 0.145$
$R_4: 0.612$
$R_5: 0.325$

With confidence $1 - \delta$, we have

$$\bar{X} - \epsilon \leq \hat{X} \leq \bar{X} + \epsilon,$$

where $\epsilon = \sqrt{\frac{\ln(1/\delta)}{2N}}$.

As examples stream in...

Monitor $\bar{X} = \text{score}_{\text{BestRule}} - \text{score}_{\text{SecondBestRule}}$

Continue until the number $N$ of examples

makes $\bar{X} > \epsilon = \sqrt{\frac{\ln(1/\delta)}{2N}}$. 
Online Rule Learning

Candidate Rules

$R_1: 0.345$

$R_2: 0.232$

$R_3: 0.145$

$R_4: 0.612$

$R_5: 0.325$

Training stream

Find the best candidate across the stream

With confidence $1 - \delta$, we have

$\bar{X} - \epsilon \leq \hat{X} \leq \bar{X} + \epsilon$, where $\epsilon = \sqrt{\frac{\ln(1/\delta)}{2N}}$

As examples stream in...

Monitor $\bar{X} = \text{score}_{\text{BestRule}} - \text{score}_{\text{SecondBestRule}}$

Continue until the number $N$ of examples makes $\bar{X} > \epsilon = \sqrt{\frac{\ln(1/\delta)}{2N}}$

Then

$\bar{X} - \epsilon > 0 \Rightarrow$

$\hat{X} > 0 \Rightarrow$

$\text{BestRule}$ is indeed the best rule, with probability $1 - \delta$. 
OLED: Online Rule Learning

\[ \text{score: 0.312} \]

fraud\((\text{CardId}, T_2)\)

\[ \text{massive\_amount(\text{CardId}, T_2)}. \]
\[ T_1 < T_2. \]

\[ \text{tiny\_amount(\text{CardId}, T_1),} \]
\[ T_2 - T_1 \leq 2 \text{ mins}. \]

Input stream
OLED: Online Rule Learning

\[
\text{fraud}(\text{CardId}, T_2) \\
\text{score: 0.987}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \text{massive\_amount(\text{CardId}, T_2)}.
\text{score: 0.312}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount(\text{CardId}, T_1)},
T_1 < T_2.
\text{score: 0.534}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount(\text{CardId}, T_1)},
T_2 - T_1 \leq 2 \text{ mins}.
\text{score: 0.023}
\]

Input stream
OLED: Online Rule Learning

fraud(CardId, T2)
score: 0.912

fraud(CardId, T2) ←
massive_amount(CardId, T2).
score: 0.345

fraud(CardId, T2) ←
tiny_amount(CardId, T1),
T1 < T2.
score: 0.567

fraud(CardId, T2) ←
tiny_amount(CardId, T1),
T2 − T1 ≤ 2 mins.
score: 0.073

Input stream

● ●
fraud(CardId, T_2)
score: 0.318

fraud(CardId, T_2) ← massive_amount(CardId, T_2),
T_1 < T_2.
score: 0.589

fraud(CardId, T_2) ← tiny_amount(CardId, T_1),
T_2 − T_1 ≤ 2 mins.
score: 0.088

OLED: Online Rule Learning
OLED: Online Rule Learning

\[ \text{fraud}(\text{CardId}, T_2) \]
\[ \text{score: 0.632} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{massive\_amount}(\text{CardId}, T_2). \]
\[ \text{score: 0.471} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount}(\text{CardId}, T_2), T_1 < T_2. \]
\[ \text{score: 0.699} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount}(\text{CardId}, T_1), T_2 - T_1 \leq 2 \text{ mins}. \]
\[ \text{score: 0.187} \]

Input stream

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OLED: Online Rule Learning

fraud(CardId, T2)
score: 0.602

fraud(CardId, T2) ←
massive_amount(CardId, T2).
score: 0.427

fraud(CardId, T2) ←
tiny_amount(CardId, T1),
T1 < T2.
score: 0.713

fraud(CardId, T2) ←
tiny_amount(CardId, T1),
T2 − T1 ≤ 2 mins.
score: 0.146

Input stream
OLED: Online Rule Learning

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \\
\text{massive\_amount}(\text{CardId}, T_2).
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \\
\text{tiny\_amount}(\text{CardId}, T_1),
T_1 < T_2.
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \\
\text{tiny\_amount}(\text{CardId}, T_1),
T_2 - T_1 \leq 2 \text{ mins}.
\]

Best rule so far; used \(\mathcal{O}(\frac{1}{\epsilon^2 \ln \frac{1}{\delta}})\) examples.
OLED: Online Rule Learning

fraud(CardId, T2)

fraud(CardId, T2) ← tiny_amount(CardId, T1), T1 < T2.
score: 0.145

fraud(CardId, T2) ← tiny_amount(CardId, T1), T1 < T2, massive_amount(CardId, T2).
score: 0.087

fraud(CardId, T2) ← tiny_amount(CardId, T1), T1 < T2, T2 − T1 ≤ 2 mins.
score: 0.203

Input stream
OLED: Online Rule Learning

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow \\
\text{massive\_amount}(\text{CardId}, T_2).
\]

\[
\begin{align*}
\text{fraud}(\text{CardId}, T_2) & \leftarrow \\
\text{tiny\_amount}(\text{CardId}, T_1), \\
T_1 & < T_2. \\
\text{score: } & 0.321
\end{align*}
\]

\[
\begin{align*}
\text{fraud}(\text{CardId}, T_2) & \leftarrow \\
\text{tiny\_amount}(\text{CardId}, T_1), \\
T_2 - T_1 & \leq 2 \text{ mins.} \\
\text{score: } & 0.312
\end{align*}
\]

\[
\begin{align*}
\text{fraud}(\text{CardId}, T_2) & \leftarrow \\
\text{tiny\_amount}(\text{CardId}, T_1), \\
T_1 & < T_2, \\
\text{massive\_amount}(\text{CardId}, T_2). \\
\text{score: } & 0.142
\end{align*}
\]

\[
\begin{align*}
\text{fraud}(\text{CardId}, T_2) & \leftarrow \\
\text{tiny\_amount}(\text{CardId}, T_1), \\
T_1 & < T_2, \\
T_2 - T_1 & \leq 2 \text{ mins.} \\
\text{score: } & 0.224
\end{align*}
\]

Input stream
fraud(CardId, T₂) ← massive_amount(CardId, T₂).

score: 0.602

fraud(CardId, T₂) ← tiny_amount(CardId, T₁),
T₁ < T₂.

score: 0.427

fraud(CardId, T₂) ← tiny_amount(CardId, T₁),
T₂ − T₁ ≤ 2 mins.

score: 0.302

fraud(CardId, T₂) ← tiny_amount(CardId, T₁),
T₁ < T₂,
massive_amount(CardId, T₂).

score: 0.253

fraud(CardId, T₂) ← tiny_amount(CardId, T₁),
T₁ < T₂,
T₂ − T₁ ≤ 2 mins.

score: 0.208
OLED: Online Rule Learning

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{massive\_amount}(\text{CardId}, T_2).
\end{align*}
\]

\[
\text{score: 0.602}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_1 &< T_2.
\end{align*}
\]

\[
\text{score: 0.427}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_2 - T_1 \leq 2 \text{ mins}.
\end{align*}
\]

\[
\text{score: 0.299}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_1 < T_2,
\end{align*}
\]

\[
\begin{align*}
\text{massive\_amount}(\text{CardId}, T_2).
\end{align*}
\]

\[
\text{score: 0.284}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_1 < T_2,
\end{align*}
\]

\[
\begin{align*}
T_2 - T_1 \leq 2 \text{ mins}.
\end{align*}
\]

\[
\text{score: 0.146}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_1 < T_2,
\end{align*}
\]

\[
\begin{align*}
\text{massive\_amount}(\text{CardId}, T_2).
\end{align*}
\]

\[
\text{score: 0.284}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_1 < T_2,
\end{align*}
\]

\[
\begin{align*}
T_2 - T_1 \leq 2 \text{ mins}.
\end{align*}
\]

\[
\text{score: 0.177}
\]

\[
\text{fraud}(\text{CardId}, T_2) \leftarrow
\begin{align*}
\text{tiny\_amount}(\text{CardId}, T_1),
\end{align*}
\]

\[
\begin{align*}
T_1 < T_2,
\end{align*}
\]

\[
\begin{align*}
\text{massive\_amount}(\text{CardId}, T_2).
\end{align*}
\]

\[
\text{score: 0.312}
\]

Input stream

● ● ● ● ●
OLED: Online Rule Learning

\( \text{fraud}(\text{CardId}, T_2) \)

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{massive\_amount}(\text{CardId}, T_2). \]

\[ \text{score: 0.602} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{massive\_amount}(\text{CardId}, T_2). \]

\[ \text{score: 0.427} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount}(\text{CardId}, T_1), T_1 < T_2. \]

\[ \text{score: 0.235} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount}(\text{CardId}, T_1), T_1 < T_2, T_2 - T_1 \leq 2 \text{ mins}. \]

\[ \text{score: 0.146} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount}(\text{CardId}, T_1), T_1 < T_2, \text{massive\_amount}(\text{CardId}, T_2). \]

\[ \text{score: 0.385} \]

\[ \text{fraud}(\text{CardId}, T_2) \leftarrow \text{tiny\_amount}(\text{CardId}, T_1), T_1 < T_2, T_2 - T_1 \leq 2 \text{ mins}. \]

\[ \text{score: 0.148} \]

Input stream

● ● ● ● ●
fraud(CardId, T_2)

fraud(CardId, T_2) ← massive_amount(CardId, T_2).

fraud(CardId, T_2) ← tiny_amount(CardId, T_1),
T_1 < T_2.

fraud(CardId, T_2) ← tiny_amount(CardId, T_1),
T_2 − T_1 ≤ 2 mins.

fraud(CardId, T_2) ←
tiny_amount(CardId, T_1),
T_1 < T_2,
massive_amount(CardId, T_2).

fraud(CardId, T_2) ←
tiny_amount(CardId, T_1),
T_1 < T_2,
massive_amount(CardId, T_2).

fraud(CardId, T_2) ←
tiny_amount(CardId, T_1),
T_1 < T_2,
massive_amount(CardId, T_2).

Best rule so far.
Empirical Analysis

- Synthetic dataset generated by Feedzai.
- Positive fraud examples for:
  - ‘Flash attack’.
  - ‘Big-after small’.
  - ‘Increasing amounts’.
  - ‘Decreasing amounts’.
  - ‘Far-away locations’.
  - ‘Card close to expire’.
- 10,000,000 transactions.
- 0.2% of the data corresponds to positive examples.
- Experiments: 10-fold cross-validation.
Empirical Analysis

<table>
<thead>
<tr>
<th>System</th>
<th>$F_1$-score</th>
<th>Precision</th>
<th>Recall</th>
<th>Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLED</td>
<td>0.830</td>
<td>0.894</td>
<td>0.776</td>
<td>21</td>
</tr>
<tr>
<td>SC</td>
<td>0.892</td>
<td>0.912</td>
<td>0.874</td>
<td>188</td>
</tr>
</tbody>
</table>

- OLED vs SC, a classic, set-cover ILP algorithm (offline learning).
- Predictive accuracy: comparable performance.
- Efficiency: OLED is much faster than offline learning.
Credit Card Fraud Management: SPEEDD Prototype

- Automated, online fraud pattern construction.
- Fraud detection (DEBS 2015).
- User Interface.
User Interface Design

- Human fraud analysts still play an important role in the process of fraud investigation.
  - Automated analysis produces a fraud score which is, in many cases, inconclusive.

- Fraud analysts interact with the SPEEDD prototype via a user interface.
  - Analysts can accept, respond to, or make suggestions and control actions.
  - Analysts may drill down to display the rationale behind the fraud alert.
### Event List

<table>
<thead>
<tr>
<th>Event Type</th>
<th>Certainty</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large amount</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>Large amount</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>Large amount</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
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</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
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<tr>
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<tr>
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<td>not investigated</td>
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<tr>
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<td>not investigated</td>
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<tr>
<td>High volume</td>
<td>60.00</td>
<td>not investigated</td>
</tr>
</tbody>
</table>

**World Map**

The world map shows data visualizations related to the event list. The map highlights regions where specific events are more prevalent. The map is interactive, allowing users to explore data by region.

**User Interface 1**

The user interface includes a dashboard with various sections for event tracking, analysis, and investigation. The dashboard integrates event logs, statistical analysis, and interactive maps for in-depth analysis.

**SPEEDO**

This section likely contains additional tools or features specific to the analysis dashboard, such as real-time data streaming or detailed input options.
User Interface 2
Human Factors Analysis: Decision Times

**UI 1**

<table>
<thead>
<tr>
<th>Confidence</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>200.00</td>
</tr>
<tr>
<td>Low</td>
<td>150.00</td>
</tr>
<tr>
<td>Med</td>
<td>100.00</td>
</tr>
<tr>
<td>Low</td>
<td>50.00</td>
</tr>
<tr>
<td>Low</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**UI 2**

<table>
<thead>
<tr>
<th>Confidence</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>22</td>
</tr>
<tr>
<td>Low</td>
<td>18</td>
</tr>
<tr>
<td>Med</td>
<td>11</td>
</tr>
<tr>
<td>Low</td>
<td>7</td>
</tr>
<tr>
<td>Low</td>
<td>4</td>
</tr>
</tbody>
</table>

**Pattern**

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Big After Small</td>
<td>18</td>
</tr>
<tr>
<td>Flash Attack</td>
<td>22</td>
</tr>
<tr>
<td>Increasing Amounts</td>
<td>16</td>
</tr>
<tr>
<td>Transactions In Faraway Places</td>
<td>22</td>
</tr>
</tbody>
</table>

**UI 1**

<table>
<thead>
<tr>
<th>Expert</th>
<th>Confidence</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>High</td>
<td>200.00</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>150.00</td>
</tr>
<tr>
<td>3</td>
<td>Med</td>
<td>100.00</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>50.00</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**UI 2**

<table>
<thead>
<tr>
<th>Expert</th>
<th>Confidence</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>High</td>
<td>22</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>18</td>
</tr>
<tr>
<td>3</td>
<td>Med</td>
<td>11</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>4</td>
</tr>
</tbody>
</table>

**Experts**

<table>
<thead>
<tr>
<th>Expert</th>
<th>Confidence</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>High</td>
<td>22</td>
</tr>
<tr>
<td>2</td>
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</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>Low</td>
<td>4</td>
</tr>
</tbody>
</table>

---

*Transactions In Faraway Places, Increasing Amounts, Flash Attack, Big After Small*
Human Factors Analysis: Modals Opened

UI 1

UI 2

pattern
Transactions In Faraway Places
Increasing Amounts
Flash Attack
Big After Small

modals opened
confidence
med
low
high

modals opened
expert
UI 1
Page 1

modals opened
expert
UI 2
Page 1

modals opened
pattern
Big After Small
Flash Attack
Increasing Amounts
Transactions In Faraway Places
Human Factors Analysis

- Analysts tend to prefer UI2:
  - place more emphasis on the relevant parts of a transaction as opposed to regional statistics.

- Analysts tend to oversample:
  - manage uncertainty
  - check for consistency in the available information.
Summary & Further Work

SPEEDD prototype:
- Automated, online fraud pattern construction.
- Fraud detection.
- User Interface.

Further work:
- Feature engineering.
- Interactive analytics.
- Alternative machine learning metrics (eg ‘money recall’).

http://speedd-project.eu/