Detecting Economic Crime using Deep Autoencoder Neural Network

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Abstract – Learning to detect economic crime in large-scale accounting data is one of the long-standing challenges in financial statement audits or fraud investigations. Currently, the majority of applied techniques refer to hand-crafted rules derived from known fraud scenarios. Whilst fairly successful, these rules exhibit the drawback that they often fail to generalise beyond known fraud scenarios and fraudsters gradually find ways to circumvent them.

To overcome this disadvantage, we propose the application of a deep autoencoder neural network to detect anomalous journal entries. We demonstrate that the trained network's reconstruction error obtainable for a journal entry can be interpreted as a highly adaptive anomaly assessment.

Experiments on three datasets of journal entries, show the effectiveness of the approach resulting in high F_1-Scores of 0.971 (train dataset) and 1.000 (test dataset). Our experiment also resulted in less false positive alerts compared to baseline methods. Initial feedback received by peers underpinned the quality of the approach in capturing highly relevant accounting anomalies.

Index Terms - Accounting Information Systems · Enterprise Resource Planning (ERP) · Computer Assisted Audit Techniques (CAATs) · Journal Entry Testing · Forensic Accounting · Fraud Detection · Forensic Data Analytics · Deep Learning

I. Motivation

The Association of Certified Fraud Examiners (ACFE) estimates that a typical organisation loses 5% of its annual revenues due to fraud [1]. Economic crime, or commonly known as fraud, refers to "the abuse of one's occupation for personal enrichment through the deliberate misuse of an organisation's resources or assets" [47].

"The median loss of a single financial statement fraud case is USD 150 thousand. The duration from the fraud perpetration till its detection was 18 months."

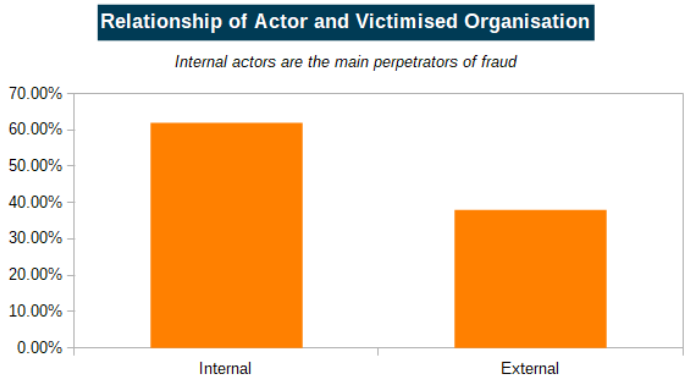
Source: Association of Certified Fraud Examiners

A similar study, conducted by PricewaterhouseCoopers (PwC) revealed that nearly 25% of respondents experienced losses between USD 100 thousand and USD 1 million due to fraud [39]. The study also showed that financial statement fraud caused by far the highest median loss surveyed fraud schemes. At the same time, organisations accelerate the digitisation and reconfiguration of business processes affecting in particular the Accounting Information Systems (AIS) or commonly known as Enterprise Resource Planning (ERP) systems [32]. SAP, one of the most common ERP providers, estimates that approximately 77% of the world's transaction touches one of their systems [41].

"49 percent of respondents said that their organisation has been a victim of fraud or economic crime in the past 24 months."

Source: PricewaterhouseCoopers

Generally, international audit standards require the direct assessment of journal entries to detect potentially fraudulent activities [2], [22]. These techniques, usually based on some known fraudulent scenarios, are often referred to as "red-flag" tests or statistical analyses such as Benford's Law [9]. However, these tests fail to generalise beyond historical fraud cases and therefore, unable to detect contemporary fraud methods.



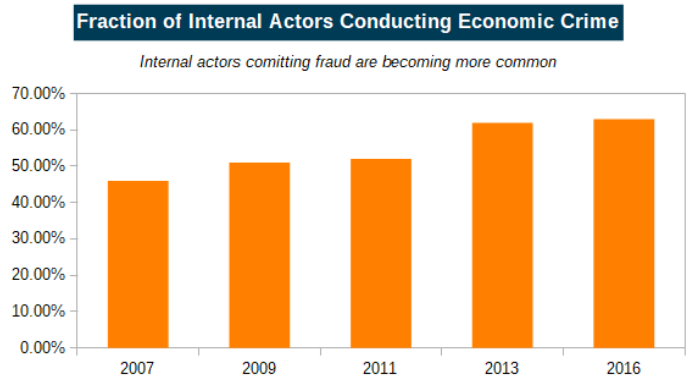
Source: PricewaterhouseCoopers

Recent developments in deep learning enables data scientists to extract complex, non-linear features, from raw sensory data, leading to advancements across many domains such as computer vision and speech recognition [29], [31], [34]. This method can supplement the accountants and forensic examiners toolbox [38].

"Our ERP applications touch 77% of global transaction revenue."

Source: SAP

In order to conduct fraud, perpetrators need to deviate from regular system usage or posting pattern. Such deviations are recorded by a very limited number of "anomalous" journal entries. Our anomaly assessment is highly adaptive and it allows to flag entries as "anomalous" if they exceed a predefined scoring threshold. We evaluate the proposed method based on three anonymised datasets of journal entries extracted from large-scale SAP ERP systems.



Source: PricewaterhouseCoopers

In section 2, we provide an overview of related works in the field of fraud detection. Section 3 follows with a description of the autoencoder network architecture and presents the proposed methodology to detect accounting anomalies. The experimental setup and results are outlined in section 4 and section 5.

II. Related Work

The task of detecting fraud and accounting anomalies has been studied by both practitioners and academia [3], [47]. Several references describe different fraud schemes and ways to detect unusual and "creative" accounting practices [44].

Fraud Detection in Enterprise Resource Planning Data

Bay, et al. used Naïve Bayes methods to identify suspicious general ledger accounts, by evaluating attributes derived from journal entries measuring any unusual general ledger account activity [8]. Their approach was enhanced by McGlohon, et al. by applying link analysis to identify groups of high-risk general ledger accounts [33].

Kahn, et al. created transaction profiles of SAP ERP users [26], [27]. Similarly, Islam, et al. used SAP R/3 system audit logs to detect known fraud scenarios and collusion fraud via a "red-flag" based matching of fraud scenarios [23].

Debreceny and Gray analysed dollar amounts of journal entries obtained from 29 US organisation [17]. In their work, they searched for violations of Benford's Law, anomalous digit combinations as well as unusual temporal pattern such as end-of-year postings [9]. More recently, Poh-Sun, et al. demonstrated the generalisation of the approach it to journal entries obtained from 12 non-US organisations [43].

Jans, et al. used latent class clustering to conduct a univariate and multivariate clustering of SAP ERP purchase order transactions [24]. The approach was enhanced by a means of process mining to detect deviating process flows in an organisation procure to pay process [25]. Transactions significantly deviating from the cluster centroids are flagged as "anomalous" and are proposed for a detailed review by auditors.

Argyrou, et al. evaluated self-organising maps to identify "suspicious" journal entries of a shipping company [6]. In their work, they calculated the Euclidean distance of a journal entry and the code-vector of a self-organising map's best matching unit. In subsequent work, they estimated optimal sampling thresholds of journal entry attributes derived from extreme value theory [7].

Concluding from the reviewed literature, the majority of references draw either on:

1. Historical accounting and forensic knowledge about various "red-flags" and fraud schemes; or
2. Traditional non-deep learning techniques

As a result, we see a demand for unsupervised and novel approaches capable to detect so far unknown scenarios of fraudulent journal entries [46].

Anomaly Detection using Autoencoder Neural Networks

Currently, autoencoder networks have been widely used in image classification, machine translation and speech processing [21], [30], [45]. Hawkins, et al. and Williams, et al. were probably the first who proposed autoencoder networks for anomaly detection [20], [48].

Since then, the ability of autoencoder networks to detect anomalous records was demonstrated in different domains such as X-ray images of freight containers, the KDD99, MNIST, CIFAR-10 as well as several other datasets from the UCI Machine Learning Repository [4], [5], [15], [50]. Zhou and Paffenroth enhanced the standard autoencoder architecture by an additional filter layer and regularisation penalty to detect anomalies [51].

Cozzolino and Verdoliva used the autoencoder reconstruction error to detect pixel manipulations of images [13]. The method was enhanced by recurrent neural networks to detect forged video sequences [16]. Paula, et al. used autoencoder networks in export controls to detect traces of money laundering and fraud by analysing volumes of exported goods [35].

III. Detection of Accounting Anomalies

In this section, we introduce the main elements of autoencoder neural networks. We furthermore describe how the reconstruction error of such networks can be used to detect anomalous journal entries in large-scale accounting data.

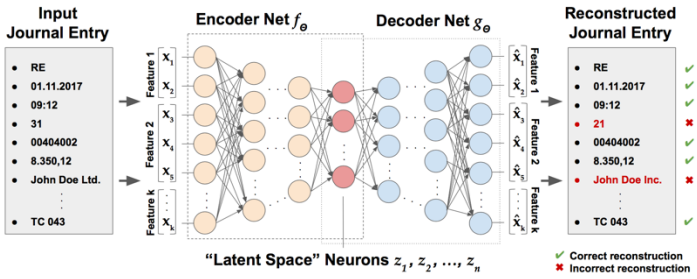
Deep Autoencoder Neural Networks

An autoencoder or replicator neural network defines a special type of feed-forward multilayer neural network that can be trained to reconstruct its input. The difference between the original input and its reconstruction is referred to as reconstruction error.

In general, autoencoder networks are comprised of two non-linear mappings referred to as an encoder and decoder network [40]. Most commonly, the encoder and the decoder are of symmetrical architecture consisting of several layers of neurons each followed by a non-linear function and shared parameters. The encoder maps an input to a compressed representation in the latent space. This latent representation is then mapped back by the decoder to a reconstructed vector of the original input space.

The autoencoder is then trained to learn a set of optimal encoder-decoder model parameters that minimises the dissimilarity of a given journal entry and its reconstruction as faithfully as

possible. For binary encoded attribute values, as used in this work, the model measures the deviation between two independent multivariate Bernoulli distribution [10].

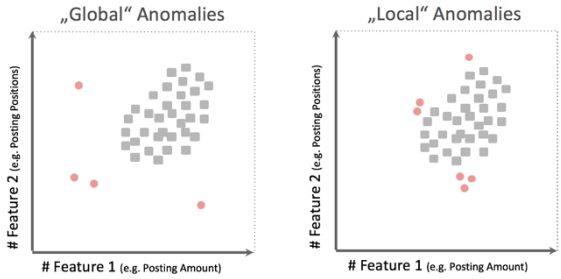


Source: Marco Schreyer and Timur Sattarov

To prevent the autoencoder from learning the identity function, the number of neurons of the networks hidden layers are reduced using a "bottleneck" architecture. Imposing such a constraint onto the network's hidden layer forces the autoencoder to learn an optimal set of parameters that result in a "compressed" model of the most prevalent journal entry attribute value distributions and their dependencies.

Classification of Accounting Anomalies

We assume that the majority of journal entries recorded relates to regular business activities. In order to conduct fraud, perpetrators need to deviate from the "normal". Such behaviour will be recorded by a very limited number of journal entries. Breunig, et al. distinguished two classes of anomalous journal entries, namely global and local anomalies [11].



Source: Marco Schreyer and Timur Sattarov

Generally, "red-flag" tests performed by auditors are designed to capture such anomalies. However, such tests often result in a high volume of false positive alerts due to events such as reverse postings, provisions and year-end adjustments usually associated with a low fraud risk. This type of anomaly is significantly more difficult to detect since perpetrators intend to disguise their activities by imitating a regular activity pattern. As a result, such anomalies usually pose a high fraud risk since they correspond to processes and activities that might not be conducted in compliance with organisational standards.

In this work, we detect any unusual value or unusual combination of values observed as anomalies. This was proposed by Das and Schneider on the detection of anomalous records in categorical datasets [14].

Scoring of Accounting Anomalies

Our score accounts for any "unusual" attribute value occurring in the journal entry. We do this by taking the reconstructed vectors from the decoder, and perform a matrix subtraction on the original input vectors. Next, we take the mean values of each journal entry and this gives us the reconstruction error.

Given that anomalous entries tend to be 0.02% of all entries recorded for the year, the model will sort the reconstruction error in descending order and focuses on the top entries. Next, a threshold score of 0.019 is applied and entries with reconstruction errors above the threshold will be flagged as anomalous.

IV. Experimental Setup and Network Training

In this section, we describe the experimental setup and model training. We evaluated the anomaly detection performance of deep autoencoder architecture based on three datasets, namely the train dataset (533,009 entries), the test dataset (33,314 entries) and the clean dataset (33,307 entries with no anomaly).

Datasets and Data Preparation

In compliance with strict data privacy regulations, all journal entry attributes have been anonymised using an irreversible one-way hash function during the data extraction process.

Let's start loading the dataset and investigate its structure and attributes:

```
# import pandas library
import pandas as pd

# load the dataset into the notebook
df_train = pd.read_csv('../data/train.csv')

# inspect the shape
print(f'Transactional dataset of
{df_train.shape[0]} rows and {df_train.shape[1]}
columns loaded')

Transactional dataset of 533009 rows and 10
columns loaded
```

Exploratory Data Analysis

The dataset contains a subset of in total 7 categorical and 2 numerical features. Below is a list of the individual features as well as a brief description of their respective semantics:

- BELNR: The accounting number
- BUKRS: The company code
- BSCHL: The posting key
- HKONT: The posted general ledger account
- PRCTR: The posted profit centre
- WAERS: The currency key
- KTOSL: The general ledger account key
- DMBTR: The amount in local currency
- WRBTR: The amount in document currency
- Label: The "ground-truth" whether the entry is regular, or anomalous "global" or anomalous "local"

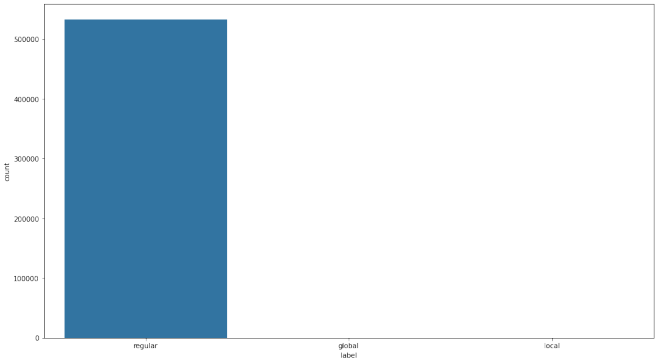
Let's also have a closer look into the top 10 rows of the dataset:

```
# inspect top rows of dataset
df_train.head(10)
```

	BELNR	WAERS	BUKRS	KTOSL	PRCTR	BSCHL	HKONT	DMBTR	WRBTR	label
0	474932	C1	C13	C1	C19	A1	B1	1438226.99	4679.0	regular
1	475702	C1	C19	C6	C64	A1	B2	3170860.50	0.0	regular
2	499810	C8	C84	C6	C67	A1	B2	139486.31	0.0	regular
3	193962	C1	C11	C1	C12	A1	B1	108669.16	0.0	regular
4	185530	C1	C18	C7	C75	A1	B2	1486691.22	0.0	regular
5	462150	C1	C17	C1	C18	A1	B1	415317.04	0.0	regular
6	449859	C1	C12	C1	C15	A1	B1	813019.77	0.0	regular
7	324486	C1	C10	C2	C20	A1	B3	804411.78	0.0	regular
8	374124	C5	C56	C1	C13	A3	B1	501968.33	59905.0	regular
9	215498	C2	C28	C1	C12	A1	B1	1184241.37	0.0	regular

There are only regular labels at the top. Let us have a closer look into the distribution of the regular versus anomalous transactions in the dataset:

```
# import matplotib and seaborn library
import matplotlib.pyplot as plt
import seaborn as sns

# display all graphs using high-quality images
%matplotlib inline
ip = get_ipython()
ibe = ip.configurables[-1]
ibe.figure_formats = {
    'pdf',
    'png'
}

# plot distribution of feature
plt.figure(figsize=(16,9))
sns.countplot(df_train.label);
```



The local and global anomalies cannot be seen by the graph above. Let us look at the value counts:

```
# number of anomalies vs. regular transactions
df_train.label.value_counts()
```

```
regular    532909
global         70
local          30
Name: label, dtype: int64
```

```
# number of anomalies vs. regular transactions
df_train.label.value_counts(normalize = True)
```

```
regular    0.999812
global     0.000131
local      0.000056
Name: label, dtype: float64
```

Similar to real world scenarios, we are facing a highly "unbalanced" dataset. Overall, the dataset contains only a fraction of 100 (0.018%) anomalous transactions. Of which, 70 (0.013%) are anomalous and 30 (0.005%) are "local" anomalies.

We will remove the label so that our model will predict without knowing the ground-truth. Similar to reality, auditors will not have entries pre-labelled whether it is anomalous or not.

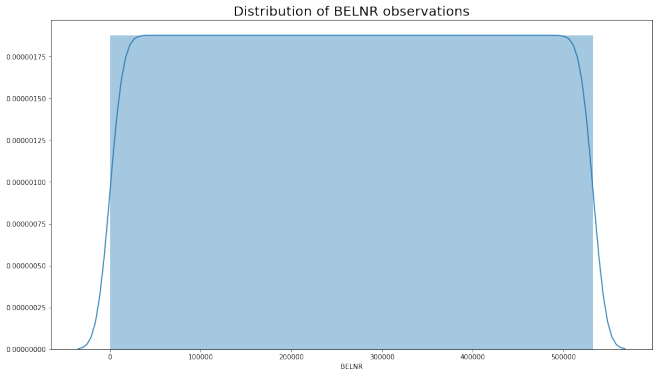
```
# remove the "ground-truth" label information
label = df_train.pop('label')
```

Categorical Features

From the initial assessment above, we can observe that the majority of attributes correspond to categorical (discrete) attribute values, e.g. the posting date, the general-ledger account, the posting type, the currency. Let us look into the distribution.

BELNR

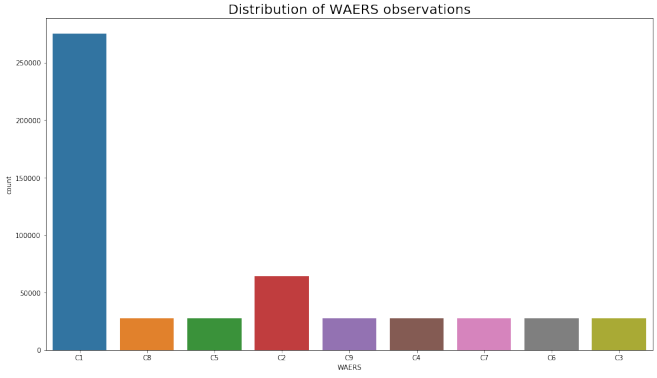
```
# plot distribution of feature
plt.figure(figsize=(16,9))
sns.distplot(df_train.BELNR)
plt.title('Distribution of BELNR observations',
fontsize = 20);
```



The distribution is even. We can conclude that the values are unique and we will not be using this feature for our model.

WAERS

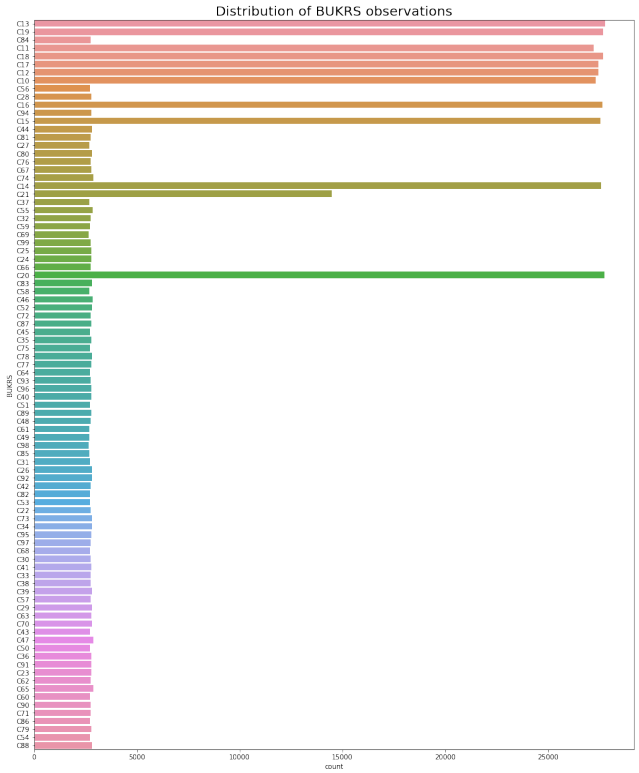
```
# prepare the plot
fig, ax = plt.subplots()
fig.set_figwidth(16)
fig.set_figheight(9)

# plot the distribution of the WAERS feature
g = sns.countplot(x=df_train.loc[label=='regular',
'WAERS'])
g.set_xticklabels(g.get_xticklabels(), rotation=0)
g.set_title('Distribution of WAERS observations',
fontsize = 20);
```



C1 appears to be the most common attribute.

BUKRS

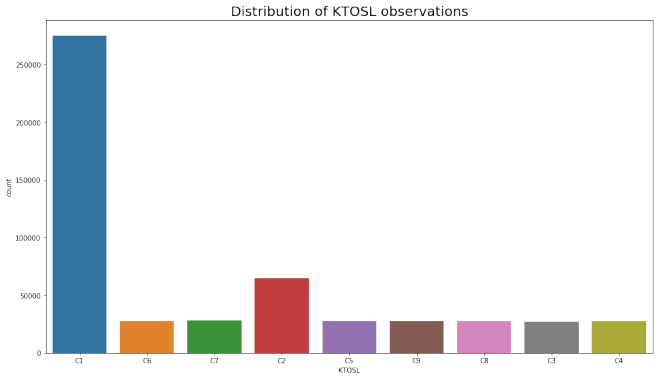
```
# prepare the plot
fig, ax = plt.subplots()
fig.set_figwidth(16)
fig.set_figheight(20)

# plot the distribution of BUKRS feature
g = sns.countplot(y=df_train.loc[label=='regular',
'BUKRS'])
g.set_yticklabels(g.get_yticklabels(), rotation=0)
g.set_title('Distribution of BUKRS observations',
fontsize = 20);
```



Most attributes are below 5,000. The most outstanding attributes are C10, C11, C12, C13, C14, C15, C16, C17, C18, C19, C20 and C21.

KTOSL

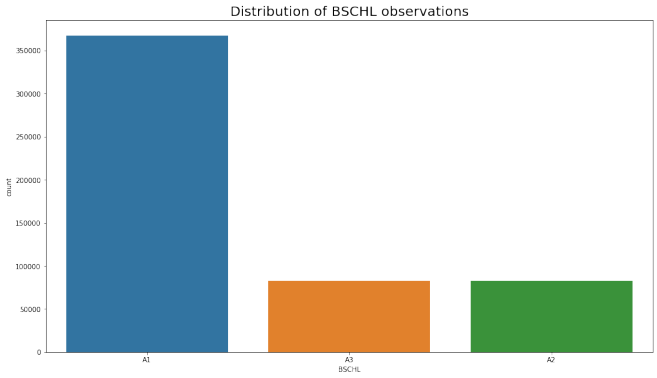
```
# prepare the plot
fig, ax = plt.subplots()
fig.set_figwidth(16)
fig.set_figheight(9)

# plot the distribution of KTOSL feature
g = sns.countplot(x=df_train.loc[label=='regular',
'KTOSL'])
g.set_xticklabels(g.get_xticklabels(), rotation=0)
g.set_title('Distribution of KTOSL observations',
fontsize = 20);
```



C1 appears to be the most common attribute.

BSCHL

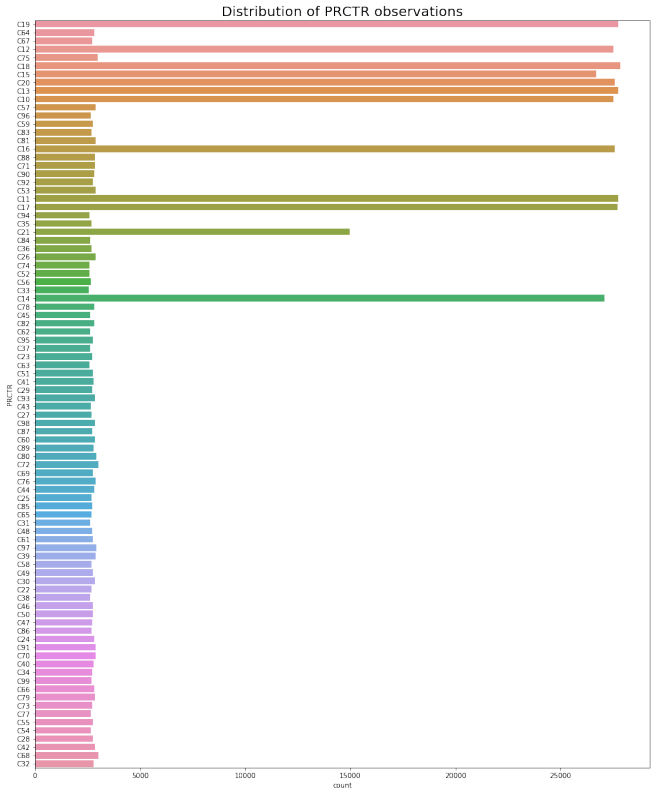
```
# prepare the plot
fig, ax = plt.subplots()
fig.set_figwidth(16)
fig.set_figheight(9)

# plot the distribution of BSCHL feature
g = sns.countplot(x=df_train.loc[label=='regular',
'BSCHL'])
g.set_xticklabels(g.get_xticklabels(), rotation=0)
g.set_title('Distribution of BSCHL observations',
fontsize = 20);
```



A1 appears to be the most common.

PRCTR

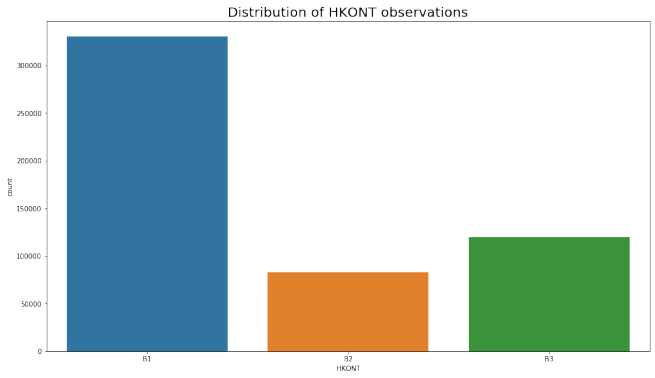
```
# prepare the plot
fig, ax = plt.subplots()
fig.set_figwidth(16)
fig.set_figheight(20)

# plot the distribution of PRCTR feature
g = sns.countplot(y=df_train.loc[label=='regular',
'PRCTR'])
g.set_yticklabels(g.get_yticklabels(), rotation=0)
g.set_title('Distribution of PRCTR observations',
fontsize = 20);
```



Most attributes are below 5,000. The most outstanding attributes are C10, C11, C12, C13, C14, C15, C16, C17, C18, C19, C20 and C21.

HKONT

```
# prepare the plot
fig, ax = plt.subplots()
fig.set_figwidth(16)
fig.set_figheight(9)

# plot the distribution of HKONT feature
g = sns.countplot(x=df_train.loc[label=='regular',
'HKONT'])
g.set_xticklabels(g.get_xticklabels(), rotation=0)
g.set_title('Distribution of HKONT observations',
fontsize = 20);
```



B1 appears to be the most common.

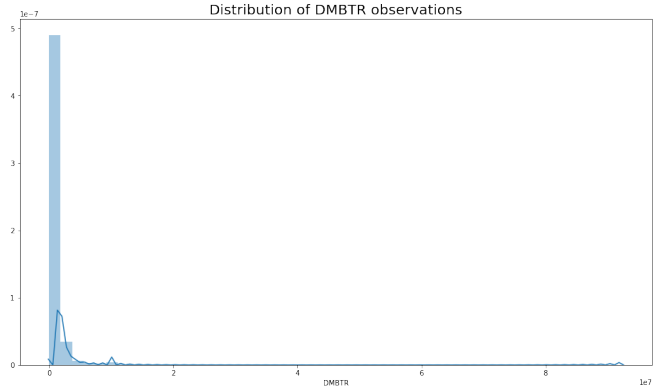
Numerical Features

Let us now inspect the distributions of the two numerical attributes contained in the transactional dataset, namely, the

1. Local currency amount DMBTR; and the
2. Document currency amount WRBTR

DMBTR

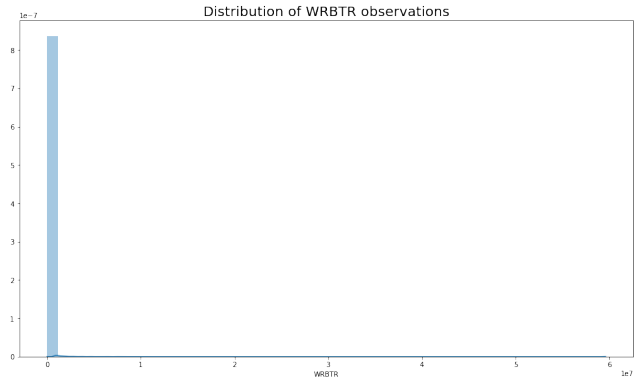
```
# plot distribution of DMBTR feature
plt.figure(figsize=(16,9))
sns.distplot(df_train.DMBTR)
plt.title('Distribution of DMBTR observations',
fontsize = 20);
```



Looks like it is heavily skewed.

WRBTR

```
# plot distribution of WRBTR feature
plt.figure(figsize=(16,9))
sns.distplot(df_train.WRBTR)
plt.title('Distribution of WRBTR observations',
fontsize = 20);
```



As expected, the distribution for both attributes are heavily tailed.

Feature Engineering

One-Hot Encoding

Unfortunately, neural networks are in general not designed to be designed to be trained directly on categorical data and require the attributes to be trained on to be numeric. One simple way to meet this requirement is by applying a technique referred to as "one-hot" encoding. Using this encoding technique, we will derive a numerical representation of each of the categorical attribute values. One-hot encoding creates new binary columns for each categorical attribute value present in the original data.

Using this technique, we will "one-hot" encode the 6 categorical attributes in the original transactional dataset. This can be achieved using the get_dummies() function.

```
# select categorical attributes to be encoded
categ_cols = ['WAERS', 'BUKRS', 'KTOSL', 'PRCTR',
'BSCHL', 'HKONT']

# encode categorical attributes into a binary one-
hot encoded representation
df_train_categ_transformed =
pd.get_dummies(df_train[categ_cols])
```

Let us inspect the top 10 sample transactions to see if we have been successful.

```
# inspect top rows
df_train_categ_transformed.head(10)
```

	WAERS_B00	WAERS_B31	WAERS_B39	WAERS_C1	WAERS_C2	WAERS_C3	WAERS_C4	WAERS_C5	WAERS_C6	WAERS_C7	...
0	0	0	0	1	0	0	0	0	0	0	...
1	0	0	0	1	0	0	0	0	0	0	...
2	0	0	0	0	0	0	0	0	0	0	...
3	0	0	0	1	0	0	0	0	0	0	...
4	0	0	0	1	0	0	0	0	0	0	...
5	0	0	0	1	0	0	0	0	0	0	...
6	0	0	0	1	0	0	0	0	0	0	...
7	0	0	0	1	0	0	0	0	0	0	...
8	0	0	0	0	0	0	0	1	0	0	...
9	0	0	0	0	1	0	0	0	0	0	...

10 rows × 616 columns

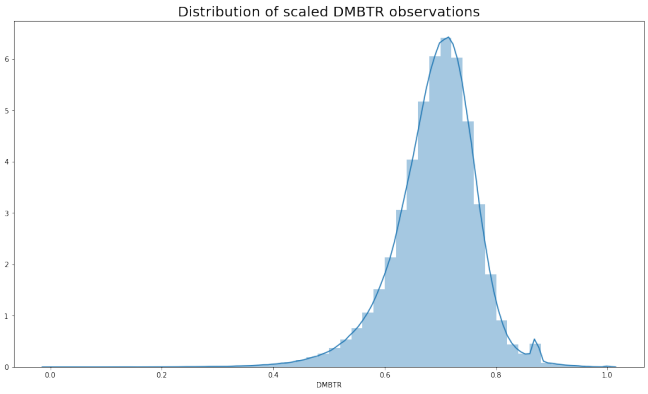
Log Transformation

Recall that the numeric features are heavily tailed. In order to process faster, we first log-scale both variables and then min-max normalise the scaled amounts to the interval [0, 1].

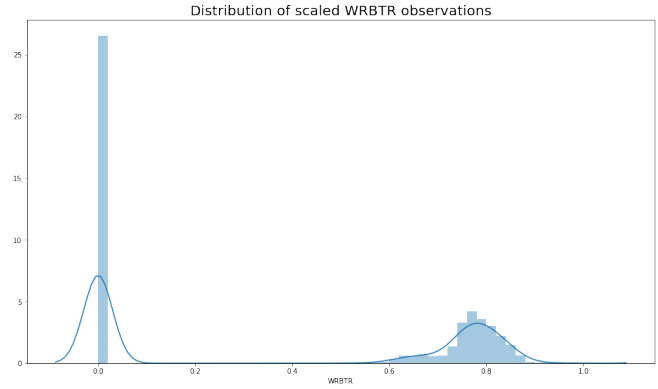
```
# import numpy library
import numpy as np

# select "DMBTR" and "WRBTR" attribute
numeric_cols = ['DMBTR', 'WRBTR']

# add a small epsilon to eliminate zero values
from data for log scaling
numeric_attr = df_train[numeric_cols] + 1e-7
numeric_attr = numeric_attr.apply(np.log)

# normalise all numeric attributes to the range
[0,1]
df_train_numeric_attr = (numeric_attr -
numeric_attr.min()) / (numeric_attr.max() -
numeric_attr.min())
```

Let us visualise the log-scaled and min-max normalised distribution of both features.

```
# plot distribution of DMBTR feature
plt.figure(figsize=(16,9))
sns.distplot(df_train_numeric_attr.DMBTR)
plt.title('Distribution of scaled DMBTR
observations', fontsize = 20);
```




```
# plot distribution of WRBTR feature
plt.figure(figsize=(16,9))
sns.distplot(df_train_numeric_attr.WRBTR)
plt.title('Distribution of scaled WRBTR
observations', fontsize = 20);
```



Merge Features

Finally, we merge both pre-processed numerical and categorical attributes into a single dataset that we will use for training our deep autoencoder neural network.

```
# merge categorical and numeric subsets
df_train_transformed =
pd.concat([df_train_categ_transformed,
df_train_numeric_attr], axis = 1)
```

Review the shape of the dataset after we applied the distinct pre-processing steps to the attributes.

```
# inspect final dimensions of pre-processed
transactional data
df_train_transformed.shape

(533009, 618)
```

Upon completion of all the pre-processing steps, we should end up with a dataset consisting of a total number of 533,009 entries (observations) and 618 features. The number of features will define the dimensionality of the input-layer and output-layer of our deep autoencoder neural network.

Exploring using Benford's Law

"Benford's law is an observation about the frequency distribution of leading digits in many real-life sets of numerical data. In sets that obey the law, the number 1 appears as the most significant digit about 30 percent of the time, while 9 appears as the most significant digit less than 5% of the time."

Source: Wikipedia

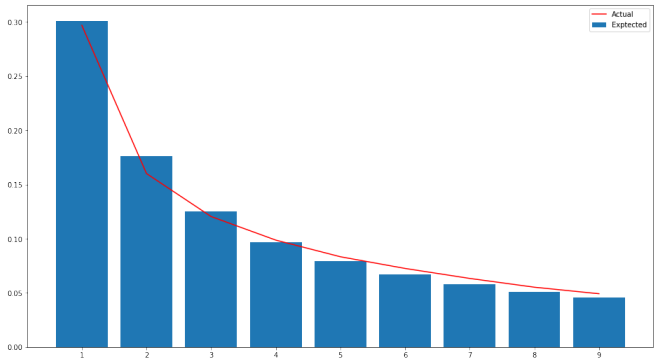
```
# make a copy of original dataset
df_train_bf = df_train.copy()

# map out the first digit and display top 10 rows
df_train_bf['FIRST_DIGIT'] =
df_train_bf.DMBTR.map(lambda a:
str(a)[0]).astype(int)
df_train_bf.head(10)
```

	BELNR	WAERS	BUKRS	KTOSL	PRCTR	BSCHL	HKONT	DMBTR	WRBTR	FIRST_DIGIT
0	474932	C1	C13	C1	C19	A1	B1	1438226.99	4679.0	1
1	475702	C1	C19	C6	C64	A1	B2	3170860.50	0.0	3
2	499810	C8	C84	C6	C67	A1	B2	139486.31	0.0	1
3	193962	C1	C11	C1	C12	A1	B1	108669.16	0.0	1
4	185530	C1	C18	C7	C75	A1	B2	1486691.22	0.0	1
5	462150	C1	C17	C1	C18	A1	B1	415317.04	0.0	4
6	449859	C1	C12	C1	C15	A1	B1	813019.77	0.0	8
7	324486	C1	C10	C2	C20	A1	B3	804411.78	0.0	8
8	374124	C5	C56	C1	C13	A3	B1	501968.33	59905.0	5
9	215498	C2	C28	C1	C12	A1	B1	1184241.37	0.0	1

```
# display the actual percentage distribution of dataset
actuals = df_train_bf.FIRST_DIGIT.value_counts(normalize=True).sort_index()
actuals
```

```
1    0.296899
2    0.160166
3    0.120465
4    0.098717
5    0.083355
6    0.072573
7    0.063357
8    0.055250
9    0.049217
Name: FIRST_DIGIT, dtype: float64
```

```
# calculate the expected distribution based on Benford's Law
digits = list(range(1,10))
benford = [np.log10(1 + 1/d) for d in digits]
plt.figure(figsize = (16,9))

# plot graph to visualise distribution
plt.bar(digits, benford, label='Exptected')
plt.plot(actuals, color='r', label='Actual')
plt.xticks(digits)
plt.legend();
```



The traditional method of Benford's Law is unable to detect the anomalies in our dataset. However, we know they exist as we have the labels.

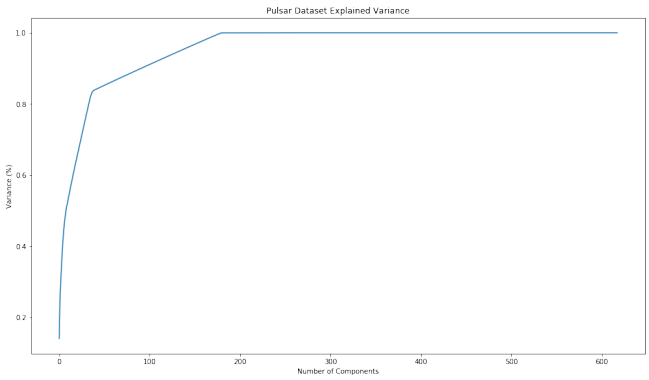
Let us proceed with the Principal Component Analysis.

Exploring using Principal Component Analysis

"Principal Component Analysis (PCA) is used to decompose a multivariate dataset in a set of successive orthogonal components that explain a maximum amount of the variance. In SciKit-Learn, PCA is implemented as a transformer object that learns components in its fit method, and can be used on new data to project it on these components"

Source: SciKit-Learn

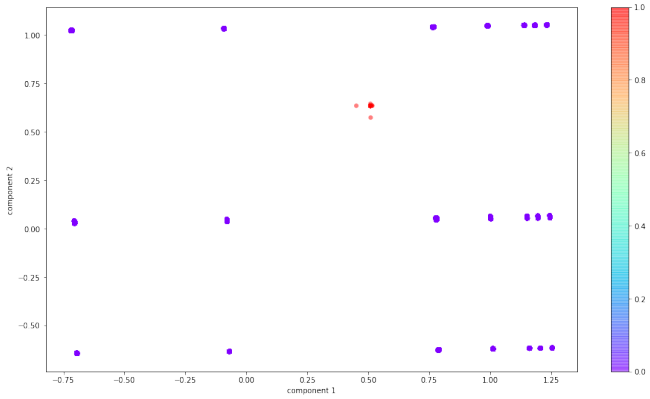
```
# create a copy for label
label_int = label.copy()

# map label as integers
label_int = label_int.map({'regular': 0, 'local': 1, 'global': 1})

# create a copy for dataset
df = df_train_transformed.copy()

# import minmaxscaler module
from sklearn.preprocessing import MinMaxScaler

# perform min-max scaling
ss = MinMaxScaler()
df_ss = ss.fit_transform(df)

# import pca module
from sklearn.decomposition import PCA

# fitting the PCA algorithm with our Data
pca = PCA().fit(df_ss)

# plotting the Cumulative Summation of the Explained Variance
plt.figure(figsize=(16,9))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Variance (%)') #for each component
plt.title('Pulsar Dataset Explained Variance')
plt.show()
```




```
# find the smallest number of components that has an explained variance ratio of at least 0.999
n_components = np.where(np.cumsum(pca.explained_variance_ratio_) >= 0.999)[0][0]
n_components
```

```
179
```

```
# perform PCA transformation using 179 components
pca = PCA(n_components=n_components)
df_pca = pca.fit_transform(df_ss)

# visualise the PCA
plt.figure(figsize=(16,9))
plt.scatter(df_pca[:, 0], df_pca[:, 1],
            c=label_int, edgecolor='none',
            alpha=0.5,
            cmap=plt.cm.get_cmap('rainbow'))
plt.xlabel('component 1')
plt.ylabel('component 2')
plt.colorbar();
```



Using PCA, we can visualise that there is an anomaly cluster in the middle. However, we are not able to determine which entries are anomalous.

Let us proceed with building the autoencoder.

Autoencoder Neural Network Training

For our architecture, we run the experiments five times using distinct parameter initialisation seeds to guarantee a deterministic range of result [49]. Furthermore, we used adaptive moment estimation and initialised the weights of each network layer [19], [28].

Increasing the number of hidden units results in faster error convergence and decreases the number of detected anomalies. Once the training has converged, the trained models are used to obtain the reconstruction errors (RE) of each journal entry.

We set the anomaly threshold as 0.019, implying that a journal entry is labelled "anomalous" if one of its attributes was not reconstructed correctly or occurs very rarely.

Preparing the Network

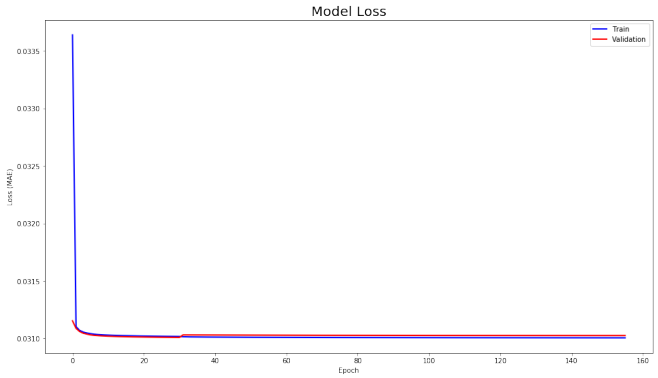
```
# Generate random seed
np.random.seed(1234)

# import regularizers, Input, Dense and Model
modules
from keras import regularizers
from keras.layers import Input, Dense
from keras.models import Model

# latent space dimension
encoding_dim = 2

# input placeholder
input_data = Input(shape = (df_ss.shape[1],))

# encoded input
encoded = Dense(512, activation = 'relu',
activity_regularizer = regularizers.l1(10e-5) )
(input_data)
encoded = Dense(256, activation='relu')(encoded)
encoded = Dense(128, activation='relu')(encoded)
encoded = Dense(64, activation='relu')(encoded)
encoded = Dense(32, activation='relu')(encoded)
encoded = Dense(16, activation='relu')(encoded)
encoded = Dense(4, activation='relu')(encoded)
encoded = Dense(encoding_dim,
activation='relu')(encoded)

# decoded input
decoded = Dense(4, activation='relu')(encoded)
decoded = Dense(16, activation='relu')(decoded)
decoded = Dense(32, activation='relu')(decoded)
decoded = Dense(64, activation='relu')(decoded)
decoded = Dense(128, activation='relu')(decoded)
decoded = Dense(256, activation='relu')(decoded)
decoded = Dense(512, activation='relu')(decoded)
decoded = Dense(df_ss.shape[1],
activation='sigmoid')(decoded)

# build autoencoder model
autoencoder = Model (input_data, decoded)

# build encoder for autoencoder model
encoder = Model (input_data, encoded)

autoencoder.compile (optimizer = 'adam', loss =
'binary_crossentropy')

# import EarlyStopping module
from keras.callbacks import EarlyStopping

# determine the earlystopping parameters
early_stopping = EarlyStopping(monitor='val_loss',
patience=5, verbose=1, mode='auto')

# import ModelCheckpoint module
from keras.callbacks import ModelCheckpoint

# create checkpoint path for each epoch
filepath="../models/{epoch:04}.hdf5"
checkpoint = ModelCheckpoint(filepath,
monitor='val_loss', verbose=1,
save_best_only=False, mode='max')

# import CSVLogger module
from keras.callbacks import CSVLogger

# create csv to save loss
csv_logger = CSVLogger("../models/history.csv",
append=True)

# print dataframe shape
print(f'Training data shape {df_ss.shape}')

Training data shape (533009, 618)

# display autoencoder architecture
autoencoder.summary()

Model: "model_1"
```

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 618)	0
dense_1 (Dense)	(None, 512)	316928
dense_2 (Dense)	(None, 256)	131328
dense_3 (Dense)	(None, 128)	32896
dense_4 (Dense)	(None, 64)	8256
dense_5 (Dense)	(None, 32)	2080
dense_6 (Dense)	(None, 16)	528
dense_7 (Dense)	(None, 4)	68
dense_8 (Dense)	(None, 2)	10
dense_9 (Dense)	(None, 4)	12
dense_10 (Dense)	(None, 16)	80
dense_11 (Dense)	(None, 32)	544
dense_12 (Dense)	(None, 64)	2112
dense_13 (Dense)	(None, 128)	8320
dense_14 (Dense)	(None, 256)	33024
dense_15 (Dense)	(None, 512)	131584

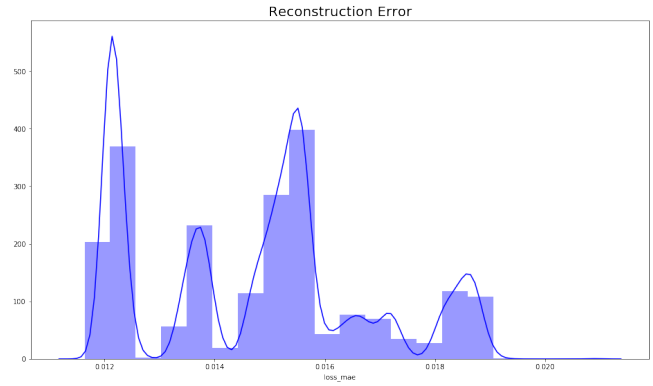
```
_________________________________________________________________
dense_16 (Dense)             (None, 618)               317034
=================================================================
Total params: 984,804
Trainable params: 984,804
Non-trainable params: 0
_________________________________________________________________
```

Training

```
epochs = 100
batch_size = 64
autoencoder_history = autoencoder.fit(
    df_ss,
    df_ss,
    epochs = epochs,
    batch_size = batch_size,
    shuffle = False,
    verbose = 2,
    validation_split = (1 / 3),
    callbacks = [
                 early_stopping,
                 checkpoint,
                 csv_logger
                 ]
).history

# plot graph for train and validation loss
fig, ax = plt.subplots(figsize = (16,9), dpi = 72)
ax.plot(autoencoder_history['loss'], 'b',
label='Train', linewidth = 2)
ax.plot(autoencoder_history['val_loss'], 'r',
label = 'Validation', linewidth = 2)
ax.set_title('Model Loss', fontsize = 20)
ax.set_ylabel('Loss (MAE)')
ax.set_xlabel('Epoch')
ax.legend(loc='best');
```




```
# create dataframe from reconstructed vectors
X_pred_train = autoencoder.predict(df_ss)
X_pred_train = pd.DataFrame(X_pred_train, columns
= df.columns)
X_pred_train.index = df.index

# create dataframe and calculate reconstruction
error
autoencoder_scored = pd.DataFrame(index =
df.index)
autoencoder_scored['loss_mse'] =
np.mean(np.abs(X_pred_train-df_ss), axis = 1)

# Plot Reconstruction Error
plt.figure(figsize=(16,9), dpi=72)
plt.title('Reconstruction Error', fontsize=20)
sns.distplot(autoencoder_scored['loss_mse'],
bins=20, kde=True, color='blue')
plt.xticks(np.arange(0,0.05,0.005));
```



Predict Anomaly

```
# determine the anomaly ratio
anomaly_ratio = 0.0002

# determine the number of rows to keep
head = int(anomaly_ratio * df_ss.shape[0])

# determine the threshold
threshold = 0.019

# create dataframe from reconstructed vector
X_pred = autoencoder.predict(df_ss)
X_pred = pd.DataFrame(X_pred, columns =
df.columns)
X_pred.index = df.index

# create dataframe of reconstruction error with
labels
autoencoder_scored = pd.DataFrame(index =
df.index)
autoencoder_scored['anomaly_score'] =
np.mean(np.abs(X_pred-df_ss), axis=1)
autoencoder_scored =
autoencoder_scored.sort_values('anomaly_score',
ascending=False).head(head)
autoencoder_scored['label'] = label

# predict anomaly
autoencoder_scored['threshold'] = threshold
autoencoder_scored['pred_anomaly'] =
(autoencoder_scored.anomaly_score >=
autoencoder_scored.threshold)
```

True Positive

```
# display true positives
autoencoder_scored[(autoencoder_scored.pred_anomal
y == True) & (autoencoder_scored.label !=
'regular')].label.value_counts()
```

```
global    70
local     30
Name: label, dtype: int64
```

False Positive (Type I Error)

```
# display false positives
autoencoder_scored[(autoencoder_scored.pred_anomal
y == True) & (autoencoder_scored.label ==
'regular')].label.value_counts()
```

```
regular    6
Name: label, dtype: int64
```

False Negative (Type II Error)

```
# display false positives
```

```
autoencoder_scored[(autoencoder_scored.pred_anomaly == False) & (autoencoder_scored.label != 'regular')].label.value_counts()
```

```
Series([], Name: label, dtype: int64)
```

```
# create dataframe for anomalous entries
df_results = autoencoder_scored[(autoencoder_scored.pred_anomaly == True)]['pred_anomaly']

df_results = pd.concat([df_train.iloc[df_results.index], df_results], axis = 1)
```

Testing the Autoencoder Neural Network

```
# load the dataset into the notebook kernel
df_test = pd.read_csv('../data/test_set_a.csv')

# remove the "ground-truth" label
if 'label' in df_test:
    label = df_test.pop('label')

# select categorical features
categ_cols = df_test.select_dtypes([np.object]).columns

# encode categorical attributes into a binary one-hot encoded representation
df_test_categ_transformed = pd.get_dummies(df_test[categ_cols])

# select numerical features
numeric_cols = df_test.select_dtypes([np.int64, np.float64, np.uint64]).columns

# add a small epsilon to eliminate zero values from data for log scaling
numeric_attr = df_test[numeric_cols] + 1e-7
numeric_attr = numeric_attr.apply(np.log)

# normalize all numeric attributes to the range [0,1]
df_test_numeric_attr = (numeric_attr - numeric_attr.min()) / (numeric_attr.max() - numeric_attr.min())

# merge categorical and numeric subsets
df_test_transformed = pd.concat([df_test_categ_transformed, df_test_numeric_attr], axis = 1)

# create a copy
df = df_test_transformed.copy()

ss = MinMaxScaler()
df_ss = ss.fit_transform(df)

# import regularizers, Input, Dense and Model modules
from keras import regularizers
from keras.layers import Input, Dense
from keras.models import Model

# latent space dimension
encoding_dim = 2

# input placeholder
input_data = Input(shape = (df_ss.shape[1],))

# encoded input
encoded = Dense(512, activation = 'relu', activity_regularizer = regularizers.l1(10e-5) )(input_data)
encoded = Dense(256, activation='relu')(encoded)
encoded = Dense(128, activation='relu')(encoded)
encoded = Dense(64, activation='relu')(encoded)
encoded = Dense(32, activation='relu')(encoded)
encoded = Dense(16, activation='relu')(encoded)
encoded = Dense(4, activation='relu')(encoded)
encoded = Dense(encoding_dim, activation='relu')(encoded)

# decoded input
decoded = Dense(4, activation='relu')(encoded)
decoded = Dense(16, activation='relu')(decoded)
decoded = Dense(32, activation='relu')(decoded)
decoded = Dense(64, activation='relu')(decoded)
decoded = Dense(128, activation='relu')(decoded)
decoded = Dense(256, activation='relu')(decoded)
decoded = Dense(512, activation='relu')(decoded)
decoded = Dense(df_ss.shape[1], activation='sigmoid')(decoded)

# create checkpoint path for each epoch
filepath="../models/test_{epoch:04}.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_loss', verbose=1, save_best_only=False, mode='max')

# create csv to save loss
csv_logger = CSVLogger("../models/test_history.csv", append=True)

epochs = 100
batch_size = 64
autoencoder_history = autoencoder.fit(
    df_ss,
    df_ss,
    epochs = epochs,
    batch_size = batch_size,
    shuffle = False,
    verbose = 2,
    validation_split = (1 / 3),
    callbacks = [
                checkpoint,
                csv_logger
                ]
).history

# create dataframe from reconstructed vector
X_pred = autoencoder.predict(df_ss)
X_pred = pd.DataFrame(X_pred, columns = df.columns)
X_pred.index = df.index

# determine the number of rows to keep
head = int(anomaly_ratio * df_ss.shape[0])

# create dataframe of reconstruction error with labels
autoencoder_scored = pd.DataFrame(index = df.index)
autoencoder_scored['anomaly_score'] = np.mean(np.abs(X_pred-df_ss), axis=1)
autoencoder_scored = autoencoder_scored.sort_values('anomaly_score', ascending=False).head(head)
autoencoder_scored['label'] = label

# predict anomaly
autoencoder_scored['threshold'] = threshold
autoencoder_scored['pred_anomaly'] = (autoencoder_scored.anomaly_score >= autoencoder_scored.threshold)
```

True Positive

```
# display true positives
autoencoder_scored[(autoencoder_scored.pred_anomaly == True) & (autoencoder_scored.label != 'regular')].label.value_counts()
```

```
global    4
local     2
Name: label, dtype: int64
```

False Positive (Type I Error)

```
# display false positives
```

```
autoencoder_scored[(autoencoder_scored.pred_anomaly == True) & (autoencoder_scored.label == 'regular')].label.value_counts()
```

```
Series([], Name: label, dtype: int64)
```

False Negative (Type II Error)

```
# display false positives
autoencoder_scored[(autoencoder_scored.pred_anomaly == False) & (autoencoder_scored.label != 'regular')].label.value_counts()
```

```
Series([], Name: label, dtype: int64)
```

```
# create dataframe for anomalous entries
df_test_results = autoencoder_scored[(autoencoder_scored.pred_anomaly == True)]['pred_anomaly']

df_test_results = pd.concat([df_train.iloc[df_test_results.index], df_test_results], axis = 1)
```

Testing with Clean Dataset

```
# load the dataset into the notebook kernel
df_test = pd.read_csv('../data/test_set_c.csv')

# remove the "ground-truth" label
if 'label' in df_test:
    label = df_test.pop('label')

# select categorical features
categ_cols = df_test.select_dtypes([np.object]).columns

# encode categorical attributes into a binary one-hot encoded representation
df_test_categ_transformed = pd.get_dummies(df_test[categ_cols])

# select numerical features
numeric_cols = df_test.select_dtypes([np.int64, np.float64, np.uint64]).columns

# add a small epsilon to eliminate zero values from data for log scaling
numeric_attr = df_test[numeric_cols] + 1e-7
numeric_attr = numeric_attr.apply(np.log)

# normalize all numeric attributes to the range [0,1]
df_test_numeric_attr = (numeric_attr - numeric_attr.min()) / (numeric_attr.max() - numeric_attr.min())

# merge categorical and numeric subsets
df_test_transformed = pd.concat([df_test_categ_transformed, df_test_numeric_attr], axis = 1)

# create a copy
df = df_test_transformed.copy()

ss = MinMaxScaler()
df_ss = ss.fit_transform(df)

# import regularizers, Input, Dense and Model modules
from keras import regularizers
from keras.layers import Input, Dense
from keras.models import Model

# latent space dimension
encoding_dim = 2

# input placeholder
input_data = Input(shape = (df_ss.shape[1],))

# encoded input
encoded = Dense(512, activation = 'relu', activity_regularizer = regularizers.l1(10e-5) )(input_data)
encoded = Dense(256, activation='relu')(encoded)
encoded = Dense(128, activation='relu')(encoded)
encoded = Dense(64, activation='relu')(encoded)
encoded = Dense(32, activation='relu')(encoded)
encoded = Dense(16, activation='relu')(encoded)
encoded = Dense(4, activation='relu')(encoded)
encoded = Dense(encoding_dim, activation='relu')(encoded)

# decoded input
decoded = Dense(4, activation='relu')(encoded)
decoded = Dense(16, activation='relu')(decoded)
decoded = Dense(32, activation='relu')(decoded)
decoded = Dense(64, activation='relu')(decoded)
decoded = Dense(128, activation='relu')(decoded)
decoded = Dense(256, activation='relu')(decoded)
decoded = Dense(512, activation='relu')(decoded)
decoded = Dense(df_ss.shape[1], activation='sigmoid')(decoded)

# create checkpoint path for each epoch
filepath="../models/clean_{epoch:04}.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_loss', verbose=1, save_best_only=False, mode='max')

# create csv to save loss
csv_logger = CSVLogger("../models/clean_history.csv", append=True)

epochs = 100
batch_size = 64
autoencoder_history = autoencoder.fit(
    df_ss,
    df_ss,
    epochs = epochs,
    batch_size = batch_size,
    shuffle = False,
    verbose = 2,
    validation_split = (1 / 3),
    callbacks = [
                 checkpoint,
                 csv_logger
                 ]
).history

# create dataframe from reconstructed vector
X_pred = autoencoder.predict(df_ss)
X_pred = pd.DataFrame(X_pred, columns = df.columns)
X_pred.index = df.index

# determine the number of rows to keep
head = int(anomaly_ratio * df_ss.shape[0])

# create dataframe of reconstruction error with labels
autoencoder_scored = pd.DataFrame(index = df.index)
autoencoder_scored['anomaly_score'] = np.mean(np.abs(X_pred-df_ss), axis=1)
autoencoder_scored = autoencoder_scored.sort_values('anomaly_score', ascending=False).head(head)
autoencoder_scored['label'] = label

# predict anomaly
autoencoder_scored['threshold'] = threshold
autoencoder_scored['pred_anomaly'] = (autoencoder_scored.anomaly_score >= autoencoder_scored.threshold)
```

True Positive

```
# display true positives
```

```
autoencoder_scored[(autoencoder_scored.pred_anomaly == True) & (autoencoder_scored.label != 'regular')].label.value_counts()
```

```
Series([], Name: label, dtype: int64)
```

False Positive (Type I Error)

```
# display false positives
autoencoder_scored[(autoencoder_scored.pred_anomaly == True) & (autoencoder_scored.label == 'regular')].label.value_counts()
```

```
regular    6
Name: label, dtype: int64
```

False Negative (Type II Error)

```
# display false positives
autoencoder_scored[(autoencoder_scored.pred_anomaly == False) & (autoencoder_scored.label != 'regular')].label.value_counts()
```

```
Series([], Name: label, dtype: int64)
```

```
# create dataframe for anomalous entries
df_clean_results = autoencoder_scored[(autoencoder_scored.pred_anomaly == True)]['pred_anomaly']

df_clean_results = pd.concat([df_train.iloc[df_clean_results.index], df_clean_results], axis = 1)
```

Overview of Autoencoder Results

	Train Dataset	Test Dataset	Clean Dataset
True Positive	100	6	0
False Negative	0	0	0
False Positive	6	0	6
True Negative	532,903	33,308	33,301
Recall	1.00	1.00	1.00
Precision	0.943	1.00	N/A
f1-Score	0.971	1.00	N/A

V. Experimental Results

This section describes the results of our evaluation. Upon successful training we evaluated the proposed scoring according to two criteria:

- Are the trained autoencoder architectures capable of learning a model of the regular journal entries and thereby detect the anomalies?
- Are the detected anomalies "suspicious" enough to be followed up by accountants or forensic examiners?

Quantitative Evaluation

To quantitatively evaluate the effectiveness of the proposed approach, a range of evaluation metrics including recall, precision and F_1-Score. The choice of F_1-Score is to account for the highly unbalanced anomalous versus non-anomalous class distribution of the datasets.

	Train Dataset	Test Dataset	Clean Dataset
Recall	1.00	1.00	1.00
Precision	0.943	1.00	N/A
f1-Score	0.971	1.00	N/A

As seen from the table above, the metrics are high for all datasets. Note that the clean dataset has no anomalies and therefore, unable to provide a precision and F_1-Score.

Overall, the deep autoencoder neural network model satisfies our quantitative evaluation.

Qualitative Evaluation

To qualitatively evaluate the character of the detected anomalies we need to review all journal entries detected by the architecture.

Train Dataset

```
df_results.head()
```

	BELNR	WAERS	BUKRS	KTOSL	PRCTR	BSCHL	HKONT	DMBTR	WRBTR	pred_anomaly
265214	390046	B00	O64	T41	Y68	H15	L79	9.244552e+07	5.958503e+07	True
303365	357271	I86	Y63	P12	V25	N67	E35	9.244553e+07	5.958505e+07	True
474924	423728	X26	I61	J33	K49	L72	I19	9.244552e+07	5.958505e+07	True
188311	442060	Q52	G37	L09	L03	C31	L31	9.244553e+07	5.958505e+07	True
507352	406276	H84	O65	X59	S63	A81	W03	9.244553e+07	5.958505e+07	True

Test Dataset

```
df_test_results.head()
```

	BELNR	WAERS	BUKRS	KTOSL	PRCTR	BSCHL	HKONT	DMBTR	WRBTR	pred_anomaly
25432	296942	C1	C10	C1	C17	A1	B1	248199.76	0.00	True
27408	517630	C1	C15	C1	C12	A1	B1	1711029.49	0.00	True
3719	523267	C1	C11	C5	C52	A1	B1	850980.66	224854.89	True
8048	200595	C1	C18	C3	C34	A1	B2	570387.47	31831.00	True
19243	513988	C9	C91	C9	C94	A2	B1	859546.05	0.00	True
16329	455485	C8	C89	C1	C11	A1	B1	1208120.19	225.00	True

Clean Dataset

```
df_clean_results.head()
```

	BELNR	WAERS	BUKRS	KTOSL	PRCTR	BSCHL	HKONT	DMBTR	WRBTR	pred_anomaly
24852	408357	C1	C19	C1	C10	A1	B1	659305.21	1093.00	True
21411	285922	C9	C97	C1	C13	A2	B1	47113.95	90129.00	True
16632	363370	C1	C18	C1	C12	A1	B1	753498.66	0.00	True
1917	222438	C7	C78	C1	C18	A3	B1	419990.04	23363.63	True
33238	498623	C7	C75	C6	C69	A3	B2	239483.33	0.00	True
26249	509490	C1	C10	C1	C14	A1	B1	282301.39	155.00	True

The majority of anomalies probably correspond to journal entries that exhibit one or two rare attribute values. This could be:

- posting errors due to wrongly used general ledger accounts;
- journal entries of unusual document types containing extremely infrequent tax codes;
- incomplete journal entries exhibiting missing currency information;
- shipments to customers that are invoiced in different than the usual currency;

- products send to a regular client but were booked to another company code;
- postings that exhibit an unusual large time lag between document date and posting date;
- irregular rental payments that slightly deviate from ordinary payments.

All of the above indicated a weak control environment around certain business processes of the investigated organization. As the dataset is anonymised as received we are unable to ascertain for a fact whether these entries were truly anomalous, other than the label provided. It requires domain knowledge and the actual dataset, both of which the author does not have.

Baseline Evaluation

There are various baseline models for us to consider, such as PCA, kMeans, One-Class Support Vector Machine, Local-Outlier Factor and DBSCAN [11], [12], [18], [36], [37], [42]. However, for simplicity of this report, we will only consider kMeans and Local-Outlier Factor. For purposes of evaluation, our metrics will be on recall, accuracy and F_1-score.

kMeans

"The KMeans algorithm clusters data by trying to separate samples in n groups of equal variance, minimising a criterion known as the inertia or within-cluster sum-of-squares."

Source: SciKit-Learn

```
# import kMeans module
from sklearn.cluster import KMeans

# initialise and fit kMeans
pca_kmeans = KMeans(n_clusters=2)
pca_kmeans.fit(df_pca)

KMeans(algorithm='auto', copy_x=True, init='k-
means++', max_iter=300, n_clusters=2, n_init=10,
n_jobs=None, precompute_distances='auto',
random_state=None, tol=0.0001, verbose=0)

# predict labels
pred_pca_kmeans = pca_kmeans.predict(df_pca)

# import confusionmatrix module
from sklearn.metrics import confusion_matrix

# display the confusion matrix
cmat = confusion_matrix(label_int.astype(int),
pred_pca_kmeans)
print(f'TN - True Negative {cmat[0,0]}')
print(f'FP - False Positive {cmat[0,1]}')
print(f'FN - False Negative {cmat[1,0]}')
print(f'TP - True Positive {cmat[1,1]}')
print(f'Accuracy Rate:
{np.divide(np.sum([cmat[0,0],cmat[1,1]]),np.sum(cm
at))}')
print(f'Misclassification Rate:
{np.divide(np.sum([cmat[0,1],cmat[1,0]]),np.sum(cm
at))}')

TN - True Negative 202666
FP - False Positive 330243
FN - False Negative 100
TP - True Positive 0
Accuracy Rate: 0.380229977354979
Misclassification Rate: 0.619770022645021

# import classification module
from sklearn.metrics import classification_report
# display the classification report
print(classification_report(label_int,
pred_pca_kmeans, digits=5))

              precision    recall  f1-score   support

           0    0.99951   0.38030   0.55097    532909
           1    0.00000   0.00000   0.00000       100

    accuracy                        0.38023    533009
   macro avg    0.49975   0.19015   0.27548    533009
weighted avg    0.99932   0.38023   0.55086    533009
```

Local Outlier Factor

"The Local Outlier Factor (LOF) algorithm computes a score reflecting the degree of abnormality of the observations. It measures the local density deviation of a given data point with respect to its neighbours. The idea is to detect the samples that have a substantially lower density than their neighbours."

Source: SciKit-Learn

```
# import localoutlierfactor module
from sklearn.neighbors import LocalOutlierFactor

# initialise and fit localoutlierfactor
pca_lof = LocalOutlierFactor(n_neighbors=30,
contamination=0.0002)
pca_lof.fit(df_pca)

LocalOutlierFactor(algorithm='auto',
contamination=0.0002, leaf_size=30,
metric='minkowski', metric_params=None,
n_jobs=None, n_neighbors=30, novelty=False, p=2)

# predict labels
pred_pca_lof = pca_lof.fit_predict(df_pca)
pred_pca_lof = pd.Series(pred_pca_lof).replace([-
1,1],[1,0])

# display the confusion matrix
cmat = confusion_matrix(label_int.astype(int),
pred_pca_kmeans)
print(f'TN - True Negative {cmat[0,0]}')
print(f'FP - False Positive {cmat[0,1]}')
print(f'FN - False Negative {cmat[1,0]}')
print(f'TP - True Positive {cmat[1,1]}')
print(f'Accuracy Rate:
{np.divide(np.sum([cmat[0,0],cmat[1,1]]),np.sum(cm
at))}')
print(f'Misclassification Rate:
{np.divide(np.sum([cmat[0,1],cmat[1,0]]),np.sum(cm
at))}')

TN - True Negative 532817
FP - False Positive 92
FN - False Negative 85
TP - True Positive 15
Accuracy Rate: 0.9996679230557083
Misclassification Rate: 0.0003320769442917474

# display the classification report
print(classification_report(label_int,
pred_pca_kmeans, digits=5))

              precision    recall  f1-score   support

           0    0.99984   0.99983   0.99983    532909
           1    0.14019   0.15000   0.14493       100

    accuracy                        0.99967    533009
   macro avg    0.57001   0.57491   0.57238    533009
weighted avg    0.99968   0.99967   0.99967    533009
```

Comparison between Autoencoder and Baseline Models

	Autoencoder	kMeans	Local Outlier Factor
True Positive	100	0	15
False Negative	0	100	85
False Positive	6	330,243	92
True Negative	532,903	202,666	532,817
Recall	1.000	0.000	0.150
Precision	0.943	0.000	0.140
f1-Score	0.971	0.000	0.145

As seen above, our autoencoder architecture is performing well above the baseline models.

VI. Conclusion and Future Work

In this work we presented a deep learning-based approach for the detection of anomalous journal entries in large scaled accounting data. Our empirical evaluation demonstrates that the reconstruction error of deep autoencoder networks can be used as a highly adaptive anomaly assessment of journal entries. In our experiments we achieved a superior F_1-Score of 0.971 in the train dataset compared to regular machine learning methods.

In this architecture, we looked only at the reconstruction errors. We could also perform clustering at the latent space and detect anomalous entries. This would be an area for future development. A python script is also made available to run the autoencoder architecture on your own dataset. A graphical user interface (GUI) would be something for the author to consider in the near future.

Given the tremendous amount of journal entries recorded by organisations annually, an automated and high precision detection of accounting anomalies can save auditors considerable time and decrease the risk of fraudulent financial statements.

Appendix

The code we used to train and evaluate our models is available at: https://github.com/AmirYunus/GA_DSI_Capstone

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