We address the problem of self-supervised learning on discrete event sequences generated by real-world users. Self-supervised learning incorporates complex information from the raw data in low-dimensional fixed-length vector representations that could be easily applied in various downstream machine learning tasks. In this paper, we propose a new method "CoLES", which adapts contrastive learning, previously used for audio and computer vision domains, to the discrete event sequences domain in a self-supervised setting.

We deployed CoLES embeddings based on sequences of transactions at the large European financial services company. Usage of CoLES embeddings significantly improves the performance of the pre-existing models on downstream tasks and produces significant financial gains, measured in hundreds of millions of dollars yearly. We also evaluated CoLES on several public event sequences datasets and showed that CoLES representations consistently outperform other methods on different downstream tasks.

CCS CONCEPTS
• Information systems → Data management systems; • Applied computing → Online banking; • Computing methodologies → Machine learning algorithms.

KEYWORDS
representation learning, metric learning, contrastive learning, self-supervised learning, event sequences, data management

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SIGMOD ‘22, June 12–17, 2022, Philadelphia, PA, USA © 2022 Association for Computing Machinery.
ACM ISBN 978-1-4503-9249-5/22/06 ... $15.00
https://doi.org/10.1145/3514221.3526129

ABSTRACT

As part of representation learning methods, data embedding aims to represent the relevant intrinsic patterns of the point or sequential data into low-dimensional fixed-length vectors capturing its "essence", that are useful in related downstream tasks,[9, 10, 25, 28, 38]. As such, pre-trained embeddings in different domains are used either as informative out-of-the-box input features for Machine Learning or Deep Learning models without extensive engineering or deep domain knowledge on the part of practitioners, or as building blocks in representations of composite multi-modal data. In big-data applications embeddings may be viewed as a learnable task-aware data compression technique, which enables storage-efficient data sharing arrangements, possibly with privacy guarantees depending on used method.

Most research and application of embedding methods, however, have been focused on the core machine learning domains, including ELMO [28] and BERT [9] in the natural language processing (NLP), CPC [38] in speech recognition, and various methods in computer vision (CV) [10, 38].

The common feature of these domains is that the data in such modalities is context sensitive: a term can be accurately reconstructed from the context-conditional language model, similarly to the way a pixel can be inferred from its neighborhood. This property underlies popular approaches for representation learning in NLP, such as BERT’s Cloze task [9], and in audio and CV, such as CPC [38].

However, not every sequential discrete data features high mutual information between a single item and its immediate neighborhood. For example, log entries, IoT telemetry, industrial maintenance, user behavior [26], travel patterns, transactional data, and other industrial and financial event sequences typically consist of interleaved relatively independent sub-streams. For example, the transactions generated either by individual or business customers feature irregular and periodic patterns, seen from the perspective of the financial services company as a stream of unlabelled and apparently unrelated events. The most state-of-the-art representation learning methods for token and sequence embedding from the NLP or CV are not guaranteed to capture the peculiarities of such financial data, which exhibits customer behavior of a certain type and constitutes
valuable information for the fraud prevention and development of efficient financial products.

In this paper, we propose a novel self-supervised method for embedding discrete event sequences, called ContraESitive Learning for Event Sequences (CoLES), which is based on contrastive learning, [14, 44], with a special data augmentation strategy. Contrastive learning aims to learn a representation \( x \mapsto M(x) \), which brings positive pairs, i.e. semantically similar objects, closer to each other in the embedding space, while negative pairs, i.e. dissimilar objects, further apart. Positive-negative pairs are obtained either explicitly from the known ground-truth target data or implicitly using self-supervised data augmentation strategies [12]. In the latter, the most common approach is conditional generation: for a given pair of distinct datapoints \( x \neq y \) the positive pairs \( (z, z') \) are sampled from the product \( p_s(z, z') = p(z | x) p(z' | x) \), while the negative pairs \(- z, z'\) are sampled from \( p_{-s}(z, z') = p(z | x) p(z' | y) \) for \( x \neq y \), where \( p(- | x) \) is a process sampling random augmentations of \( x \).

As a self-supervised sequence embedding method, CoLES uses a novel augmentation algorithm, which generates sub-sequences of observed event sequences and uses them as different high-dimensional views of the object (sequence) for contrastive learning. The proposed generative process is specifically designed to address the observed interleaved periodicity in financial transaction event sequences, which is the primary application of our method (see Section 4.3). Representations learnt by CoLES can be used as feature vectors in supervised-domain-related tasks [25, 35, 48], e.g. fraud detection or scoring tasks based on transaction history, or they can be fine-tuned for out-of-domain tasks [47].

We have applied CoLES to four publicly available datasets of event sequences from different domains, such as financial transactions, retail receipts and game assessment records. As we show in the experimental section, CoLES produces representations, which achieve strong performance results, comparable to the hand-crafted features produced by domain experts. We also demonstrate that the fine-tuned CoLES representations consistently outperform representations produces by alternative methods. Additionally, we deployed CoLES embeddings in several applications in our organization and tested the method against the models currently used in the company. Experimental results, demonstrate CoLES embeddings significantly improve the performance of the pre-existing models on the downstream tasks, which resulted in significant financial gains for the company.

This paper makes the following contributions. We

1. present CoLES, a self-supervised method with a novel augmentation method, which adapts contrastive learning to the discrete event sequence domain;
2. demonstrate that CoLES consistently outperforms existing supervised, self-supervised and semi-supervised learning baselines adapted to the event sequence domain;
3. present the results of applying CoLES embeddings in the real-world scenario and show that the proposed method can be of significant value for the day-to-day modelling in financial services industry.

The rest of the paper is organized as follows. In the next section, we discuss related studies on self-supervised and contrastive learning. In Section 3, we introduce our new method CoLES for discrete event sequences. In Section 4, we demonstrate that CoLES outperforms several strong baselines including previously proposed contrastive learning methods adapted to event sequence datasets. Section 5 is dedicated to the discussion of our results and conclusions. We provide the source code for all the experiments on public datasets described in this paper.\(^1\)

\(^1\)https://github.com/dllllb/coles-paper

2 RELATED WORK

Contrastive learning has been successfully applied to constructing low-dimensional representations (embeddings) of various objects, such as images [7, 32], texts [30], and audio recordings [41]. Although the aim of these studies is to identify the object based on its sample [18, 32, 41], these supervised approaches are not applicable to our setting, since their training datasets explicitly contain multiple independent samples per each particular object, which form positive pairs as a critical component for learning.

For situations when positive pairs are not available or their amount is limited, synthetic data generation and augmentation techniques could be employed. One of the first such frameworks was proposed by Dosovitskiy et al. [10], who introduce surrogate classes by randomly augmenting the same image. Several recent works, e.g. [2, 4, 15], extended this idea by applying contrastive learning methods (see [12]). Contrastive Predictive Coding (CPC) is a self-supervised learning approach proposed for non-discrete sequential data in [38]. The CPC employs an autoregressive predictive model of the input sequence in order to extract meaningful latent representations, and as such can be adapted the domain of discrete event sequences (see Section 4.2 for comparison with CoLES).

Several publications consider self-supervision for user behavior sequences in the recommender system and user behavior analysis domains. CPC-like approach for self-supervised learning on user click histories is proposed in [51], while [23] use an auxiliary self-supervised sequence-to-sequence loss term. In [52], it was proposed to use “Cloze” task from BERT [9] for self-supervision on purchase sequences. A SimCLR-like approach for text-based tasks and tabular data was adapted in [45]. In [53] authors propose an unsupervised autoregressive method to produce embeddings of attributed sequences where a sequence of categorical tokens has additional global attributes. The aforementioned works consider sequences of “items”, where each element is an item identifier. We consider more complex sequences of events where an element of the sequence consists of several categorical and numerical fields.

There are papers dedicated to supervised learning for discrete event sequences, e.g. [1, 3, 34, 36, 42], but self-supervised pre-training is not used in those works.

3 PROBLEM FORMULATION AND OVERVIEW OF THE COLES METHOD

3.1 Problem formulation

While the method proposed in this study could be studied in different domains, we focus on discrete sequences of events. Assume there are some entities \( e \) and that each entity’s lifetime activity is observed as a sequence of events \( x_e := \{x_e(t)\}_{t=1}^{T_e} \). Entities could be people or organizations or some other abstractions. Events \( x_e(t) \)
may have any nature and structure (e.g., transactions of a client, click logs of a user), and their components may contain numerical, categorical, and textual fields (see datasets description in Section 4).

According to theoretical framework of contrastive learning proposed in [31], each entity \(e\) is a latent class, which is associated with a distribution \(P_e\) over its possible samples (event sequences). However, unlike the problem setting of [31], we have no positive pairs, i.e., pairs of event sequences representing the same entity \(e\). Instead, only one sequence \(x_e\) is available for the entity \(e\). Formally, each entity \(e\) is associated with a latent stochastic process \(\{X_e(t)\}_{t \geq 1}\), and we observe only a single finite realisation \(\{x_e(t)\}_{t=1}^T\) of it. Our goal is to learn an encoder \(M\) that maps event sequences into a feature space \(\mathbb{R}^d\) in such a way that the obtained embedding \(x_e \mapsto c_e = M(x_e) \in \mathbb{R}^d\) encodes the essential properties of \(e\) and disregards irrelevant noise contained in the sequence. That is, the embeddings \(M((x'))\) and \(M((x''))\) should be close to each other, if \(x'\) and \(x''\) were paths generated by the same process \(\{X_e(t)\}\), and further apart, if generated by distinct processes.

The quality of representations can be examined by downstream tasks in the two ways:

1. \(c_e\) can be used as a feature vector for a task–specific model (see Figure 1, Phase 2a).
2. encoder \(M\) can also be (jointly) fine-tuned [47] (see Figure 1, Phase 2b).

### 3.2 Sampling of surrogate sequences as an augmentation procedure

When there is no sampling access to the latent processes \(\{X_e(t)\}\), one could employ synthetic augmentation strategies, which are akin to bootstrapping. Most augmentation techniques proposed for continuous domains, such as image displacement, color jitter or random gray scale in CV, [12], are not applicable to discrete events. Thus, generating sub-sequences from the same event sequence \(\{x_e(t)\}\), could be used as a possible augmentation. The idea proposed below resembles the bootstrap method, [11], which, roughly, posits that the empirical distribution induced by the observed sample of independent datapoints is a suitable proxy for the distribution of the population. In our setting, however, the events are not independent observations, which prompts us to rely on different data assumptions.

The key property of event sequences that represent lifetime activity is periodicity and repeatability of its events (see Section 4.0.2 for the empirical observations of these properties for the considered datasets). This motivates the Random slices sampling method applied in CoLES, as presented in Algorithm 1. Sub-sequences \(\{x_e\}\) are sampled from a given sequence \(\{x_e(t)\}\) as continuous segments, “slices”, using the following three steps. First, the length of the slice is chosen uniformly from the admissible values. Second, too short (and, optionally, too long) sub-sequences are discarded. Third, the starting position is uniformly chosen from all possible values. The overview of the CoLES method is presented in Figure 1.

**Algorithm 1:** Random slices sub-sequence generation strategy

**hyperparameters:** \(m, M\): minimal and maximal possible length of a sub-sequence; \(k\): number of samples.

**input:** A sequence \(S = \{z_{ij}\}_{j=1}^n\) of length \(T\).

**output:** \(S\): sub-sequences of \(S\).

for \(i \leftarrow 1\) to \(k\) do

| step | action |
|------|--------|
| if \(T_i \in [m, M]\) then |
| Generate a random integer \(s\) from \([0, T - T_i]\); |
| Add the slice \(\tilde{S}_i := \{z_{s+j}\}_{j=0}^{T_i-1}\) to \(S\); |
| end |

**end**

### 3.3 Model training

**Batch generation.** The following procedure creates a batch for CoLES. \(N\) initial sequences are randomly taken and \(K\) sub-sequences are produced for each of one. Pairs of sub-sequences of from same sequence are used as positive samples and pairs from different sequences – as negatives.

In the experiment section we consider several baseline empirical strategies for the sub-sequence generation to compare with Algorithm 1. The details of the comparison are presented in Section 4.2.1.
Contrastive loss \ We consider a classical variant of the contrastive loss, proposed in \cite{Hadsell2006}, which minimizes the objective

\[
\mathcal{L}_{uw}(M) = \frac{1}{2} d_M(u, v)^2 + \frac{1}{2} (1 - Y_{uw}) \mathop{\max}\{0, \rho - d_M(u, v)\}^2,
\]

with respect to \(M: \mathbb{X} \rightarrow \mathbb{R}^S\), where \(d_M(u, v) = d(c_u, c_v)\) is the distance between embeddings of the pair \((u, v)\), \(c_u = M(\tilde{x}_u(t))\), \(Y_{uw}\) is a binary variable identifying whether the pair \((u, v)\) is positive, and \(\rho\) is the soft minimal margin between dissimilar objects. The second term encourages separation of the embeddings in negative pairs and prevents mode collapse in \(M\), when the entities are mapped to the same point in the embedding space. \(d(a, b)\) is the Euclidean distance, \(d(a, b) = \sqrt{\sum_k (a_k - b_k)^2}\), as proposed in \cite{Hadsell2006}. The sequences \(\{\tilde{x}_u(\tau)\}\) and \(\{\tilde{x}_v(\tau)\}\) of a pair with \(Y_{uw} = 0\) are obtained through random slice generation (Algorithm 1) from the same observation \(\{x_e(\tau)\}\), while in pairs with \(Y_{uw} = 0\) the sequences are sampled from \(\{x_e(\tau)\}\) and \(\{x_{\bar{g}}(\tau)\}\), respectively, for \(e \neq g\).

In the experiment section we compare the basic variant of the contrastive loss with alternative variants. The results of the comparison is presented in Section 4.2.1.

Negative sampling. One challenge in contrastive learning approach is that positive pairs are overwhelmed by potential negative pairs. Furthermore, some of negative pairs are distant enough, to not provide any valuable feedback through \(\mathcal{L}\) to \(M\) during training. \cite{Gutmann2010, Wang2019}. We compare the common negative sampling approaches in Section 4.2. Due to certain negative sampling approaches begin distance-aware and in order to make the overall distance computation less inefficient we restrict the encoder \(M\) to the class of maps that output unit-norm vectors in \(\mathbb{R}^d\). Therefore the pairwise distance \(d_M(u, v)^2\) is just \(2 - 2c_u^\top c_v\), which only requires pairwise dot products between embeddings \(c_v = M(\tilde{x}_u(t))\).

3.4 Encoder architecture

Embedding a sequence of events into a vector of fixed size requires encoding individual events followed by aggregating the entire sequence. The composite encoder model \(M\) in CoLES is of the form \(M(\{x_t\}) := \phi_{\text{seq}}(\phi_{\text{evt}}(x_T))\), where \(\phi_{\text{evt}}\) and \(\phi_{\text{seq}}\) are event- and sequence-level embedding networks, respectively, trained in an end-to-end manner to minimize the contrastive loss \(\mathcal{L}(M)\).

The event encoder \(\phi_{\text{evt}}\) takes a set of attributes of each event \(x_T\) and outputs its intermediate representation in \(\mathbb{R}^d:\ z_t = \phi_{\text{evt}}(x_T)\). This encoder consists of several linear layers, for embedding one-hot encoded categorical attributes, and batch normalization layers, applied to numerical attributes of events. Outputs of these layers are concatenated to produce the event embedding \(z_t\).

The sequence encoder \(\phi_{\text{seq}}\) takes the intermediate representations of the events \(z_T = z_1, z_2, \cdots, z_T\) and outputs the representation \(c_T\) of their sequence up to the time \(t: c_t = \phi_{\text{seq}}(z_1, t)\). The last \(c_T\) is used as the embedding of the whole event sequence. In our experiments, we use GRU, \cite{Graves2005}, a recurrent network which demonstrates robust performance on the sequential data. \cite{Cho2014}. In this case, \(\phi_{\text{seq}}\) is computed by the recurrence \(c_t = \text{GRU}(z_{t+1}, c_t)\) starting from a learnt \(c_0\). We note, that other architectures are possible, including LSTM and transformers, \cite{Sutskever2014, Vaswani2017} (see Section 4.2.1).

To summarise, CoLES consists of three major ingredients: the event sequence encoder, the positive and negative pair generation strategy, and the loss function for contrastive learning.

4 EXPERIMENTS

4.0.1 Datasets. We compare our method with existing baselines on several publicly available datasets of event sequences from various data science competitions. We chose datasets with sufficient amounts of discrete events per user.

Age group prediction competition\footnote{https://ods.ai/competitions/sherbank-sirius-lesson} \ The dataset of 44M anonymized credit card transactions representing 50K individuals was used to predict the age group of a person. The multiclass target label is known only for 30K records, and within this subset the labels are balanced. Each transaction includes the date, type, and amount being charged.

Churn prediction competition\footnote{https://boosters.pro/championship/resbank1/} \ The dataset of 1M anonymized card transactions representing 10K clients was used to predict churn probability. Each transaction is characterized by date, type, amount and Merchant Category Code. The binary target label is known only for 5K clients, and labels are almost balanced.

Assessment prediction competition\footnote{https://www.kaggle.com/c/data-science-bowl-2019} \ The task is to predict the in-game assessment results based on the history of children’s gameplay data. Target is one of four grades, with shares 0.50, 0.24, 0.14, 0.12. The dataset consists of 12M gameplay events combined in 330K gameplay represents 18K children. Only 17.7K gameplay are labeled. Each gameplay event is characterized by a timestamp, an event code, an incremental counter of events within a game session, time since the start of the game session, etc.

Retail purchase history age group prediction\footnote{https://ods.ai/competitions/xl-retailhero-uplift-modeling} \ The task is to predict the age group of a client based on their retail purchase history. The age group is known for all clients. The group ratio is balanced in the dataset. The dataset consists of 45.8M retail purchases representing 400K clients. Each purchase is characterized by time, product level, segment, amount, value, loyalty program points received.

Scoring competition\footnote{https://boosters.pro/championship/alfabattle2/overview} \ The dataset of 443M anonymized credit card transactions representing 1.47M persons was used to predict the probability of credit product default. The label is known for 0.96M persons. The default rate is 2.76% in the dataset. Each transaction includes the set of date features, set of type features, and amount being charged.

4.0.2 Repeatability and periodicity of the datasets. To check that considered datasets follow our repeatability and periodicity assumption made in Section 3.2 we performed the following experiments. We measure the KL-divergence between two kinds of samples: (1) between random slices of the same sequence, generated using a modified version of Algorithm 1 where overlapping events are dropped, and (2) between random sub-samples taken from different sequences. The results are displayed in Figure 2, which shows that the KL-divergence between sub-sequences of the same sequence of events is relatively small compared to the typical KL-divergence between sub-samples of different sequences of events. This observation supports our repeatability and periodicity assumption. Also note that additional plot (2d) is provided as an example for data without any repeatable structure.
Figure 2: Periodicity and repeatability of the data. KL-divergence between event types of two random sub-sequences from the same sequence is compared with KL-divergence between sub-sequences of different sequences. Additional plot (2d) is provided as an example for data without any repeatable structure.

Table 1: Hyper-parameters for CoLES training

| Dataset      | Age   | Churn | Assess | Retail |
|--------------|-------|-------|--------|--------|
| Embedding size | 800   | 1024  | 100    | 800    |
| Learning rate | 0.001 | 0.004 | 0.002  | 0.002  |
| N samples in batch | 64    | 128   | 256    | 256    |
| N epochs     | 150   | 60    | 100    | 30     |
| Min sequence length | 25    | 15    | 100    | 30     |
| Max sequence length | 200   | 150   | 500    | 180    |
| Encoder      | GRU   | LSTM  | GRU    | GRU    |

For all methods, a random search on 5-fold cross-validation over the training set is used for hyper-parameter selection. The number of sub-sequences generated for each sequence was always 5 for each dataset.

4.0.3 Dataset split. For each dataset, we set apart 10% persons from the labeled part of the data as the test set, used for evaluation. The remaining 90% of labeled data and unlabeled data constitute our training set used for learning. The hyper-parameters of each method were selected by random search over 5-fold cross-validation on the training set.

For the learning of semi-supervised/self-supervised techniques (including CoLES), we used all transactions of training sets including unlabeled data. The unlabelled parts of the datasets were ignored while training supervised models.

4.0.4 Training performance. Neural networks were trained on a single Tesla P-100 GPU card. At the training stage of CoLES, each single training batch is processed in 142 milliseconds. For example, in the age group prediction dataset a single batch contains 64 unique individuals with five sub-sequences per each, i.e. 320 training sub-sequences in total, each averaging 90 transactions, which means that each batch contains about 28800 transactions.

4.0.5 Hyperparameters. Unless specified otherwise, we use contrastive loss and random slices pair generation strategy for CoLES in our experiments (see Section 4.2 for motivation). The final set of hyper-parameters used for CoLES is shown in the Table 1.

4.1 Baselines

4.1.1 LightGBM. The Gradient Boosting Machine (GBM) [13] is generally considered a strong baseline in cases of tabular data with heterogeneous features,[27, 40, 43, 49]. In our experiments we use LightGBM [20] as a model for the downstream task (see Figure 1, Phase 2a) and consider alternative input features: (1) the vector of of hand-crafted aggregate features produced from the raw transactional data, or (2) the embedding of the sequence of transactions, produced by the encoder network (see Section 3.4). For the latter the encoder model is trained in the self-supervised fashion either with CoLES or one of its alternatives, described in the Section 4.1.3.

4.1.2 Hand-crafted features. All attributes of each transaction are either numerical, e.g. amount, or categorical, e.g. merchant category (MCC code), transaction type, etc. For the numerical attributes we apply aggregation functions, such as ‘sum’, ‘mean’, ‘std’, ‘min’, ‘max’, over all transactions per sequence. For example, if we apply ‘sum’ over the numerical field ‘amount’ we get a feature ‘sum of all transaction amounts per sequence’. Categorical attributes are aggregated in a slightly different way. We group the transactions separately by every unique value of each categorical attribute and apply an aggregation function, such as ‘count’, ‘mean’, ‘std’ over all numerical attributes. For example, if we apply ‘mean’ for the numerical attribute ‘amount’ grouped by categorical attribute ‘MCC code’ we obtain one feature ‘mean amount of all transactions for the specific MCC code’ per sequence.

4.1.3 Self-supervised baselines. We compared CoLES method against major existing approaches to self-supervised embedding, which are applicable to the event sequence data.

NSP. We consider a simple baseline inspired by the next sentence prediction task in BERT [9]. Specifically, we generate two sub-sequences A and B in a way that 50% of the time B follows A in the same sequence (positive pair), and 50% of the time it is a random fragment from another sequence (negative pair).

SOP. Another baseline is the same as sequence order prediction task from ALBERT [22], which uses two consecutive sub-sequences...
as a positive pair, and two consecutive sub-sequences with swapped order as a negative pair.

**RTD.** The replaced token detection approach from ELECTRA [8] could be also adapted to event sequences. To get this baseline, we replaced 15% of events from the sequence with random events, taken from other sequences and train a model to predict whether an event is replaced or not.

**CPC.** Additionally, we compare against Contrastive Predictive Coding (CPC) [38] – a self-supervised learning method that demonstrates state-of-the-art performance on sequential data audio, computer vision, reinforcement learning and recommender systems domains, [51].

### 4.2 Results

#### 4.2.1 Discussion of design choices. To evaluate the proposed method of sub-sequence generation (see Section 3.2) we compared it with two alternatives: (1) The random sampling without replacement strategy, similar to [45], and (2) random disjoint samples strategy, which resembles the generation proposed in [23]. The first approach generates a non-contiguous sub-sequence of events, by repeatedly drawing a random event from the sequence without replacement preserving the in-sequence order of the sampled events. The second approach produces sub-sequences by the randomly splitting the initial sequence into several non-overlapping contiguous segments. The motivation is that overlaps between sub-sequences may possibly lead to overfitting, since the exact sub-sequences of events are the same and may be “memoized” by the encoder without learning underlying similarities.

The results of the comparison are presented in Table 2. The proposed strategy of generating random sub-sequence slices consistently outperforms alternatives.

We evaluated several contrastive learning loss functions that showed promising performance on different datasets [19] and some classical variants, namely: contrastive loss [14], binomial deviance loss [46], triplet loss [17], histogram loss [37], and margin loss [24]. The results of comparison are shown in Table 4. Noteworthy, although the contrastive loss can be considered as the basic variant of contrastive learning, yet it still manages to achieve strong results on the downstream tasks. We speculate that an increase in the model’s performance on contrastive learning task does not always lead to increased performance on downstream tasks.

We also compared popular negative sampling strategies (distance-weighted sampling [24], and hard-negative mining [32]) with random negative sampling strategy (see Table 5). We can observe that hard negative mining leads to a measurable increase in quality on downstream tasks in comparison to random negative sampling.

Yet another possible design choice of the method is the encoder architecture. We compared several popular options for the sequence encoder: GRU [5], LSTM [16] and Transformer [39]. Table 3 shows that the choice of the encoder architecture has little effect on the performance of the proposed method.

Figure 3 shows that the performance on the downstream task exhibits diminishing gains as the dimensionality of the embedding increases. These results can be interpreted through the lens of the bias-variance trade-off: when the dimensionality is too low, too much information is discarded (high bias), however, when it is too high, then much more irrelevant noise seeps into the embedding (high variance). Note, that the training time and the memory consumption scale linearly with the embedding size.

#### 4.2.2 Self-supervised embeddings. We compared CoLES with baselines described in Section 4.1 in two scenarios. First, we compared

---

**Table 2: Comparison of batch generation strategies**

| Sample method       | Age Accuracy | Churn AUROC | Assess Accuracy | Retail Accuracy |
|---------------------|--------------|-------------|-----------------|-----------------|
| Random samples      | 0.613        | 0.820       | 0.563           | 0.523           |
| Random disjoint samples | 0.619   | 0.819       | 0.563           | 0.505           |
| Random slices       | 0.639        | 0.823       | 0.618           | 0.542           |

5-fold cross-validation metric is shown

**Table 3: Comparison of encoder types**

| Dataset      | Age group Accuracy | Churn AUROC | Assess Accuracy | Retail Accuracy |
|--------------|--------------------|-------------|-----------------|-----------------|
| LSTM         | 0.621              | 0.823       | 0.620           | 0.535           |
| GRU          | 0.638              | 0.812       | 0.618           | 0.542           |
| Transformer  | 0.622              | 0.780       | 0.542           | 0.499           |

5-fold cross-validation metric is shown

**Table 4: Comparison of contrastive learning losses**

| Dataset      | Age group Accuracy | Churn AUROC | Assess Accuracy | Retail Accuracy |
|--------------|--------------------|-------------|-----------------|-----------------|
| Contrastive | 0.639              | 0.823       | 0.618           | 0.542           |
| Binomial deviance | 0.621          | 0.769       | 0.589           | 0.535           |
| Histogram    | 0.632              | 0.815       | 0.615           | 0.533           |
| Margin       | 0.638              | 0.823       | 0.612           | 0.541           |
| Triplet      | 0.636              | 0.781       | 0.600           | 0.541           |

5-fold cross-validation metric is shown

**Table 5: Comparison of negative sampling strategies**

| Dataset                  | Age group Accuracy | Churn AUROC | Assess Accuracy | Retail Accuracy |
|--------------------------|--------------------|-------------|-----------------|-----------------|
| Hard negative mining     | 0.639              | 0.823       | 0.618           | 0.542           |
| Random negative sampling | 0.626              | 0.815       | 0.593           | 0.530           |
| Distance-weighted sampling | 0.629            | 0.821       | 0.603           | 0.536           |

5-fold cross-validation metric is shown
embeddings produced by CoLES with other types of embeddings, including the manually created ones, by using them as input into a downstream LightGBM model (see Figure 1, Phase 2a), trained independently from the sequence encoder. As Table 6 demonstrates, the sequence embeddings, produced by CoLES, perform on par and sometimes even better than manually engineered features. Furthermore, CoLES consistently outperforms other self-supervised baselines on the four out of the five considered datasets.

On the scoring dataset, which is larger than the other datasets, CoLES, CPC, and RTD, outperform the hand-crafted baseline. The autoregressive nature of the CPC aligns well with the credit scoring task, for which the more recent the information the more relevant it is to the target. The RTD embeddings are also effective for credit scoring, since the method relies on anomaly detection.

Simple hand-crafted features can achieve competitive results if the events have a clear structure for designing them, e.g., it is straightforward to compute the group-wise aggregate statistics of historical data based on some attribute. In the commercial settings (Section 4.3) the situation may be different: it is non-trivial to manufacture meaningful features for transactions of legal entities, since it is not clear what the natural groupings are. We discuss the difference between simple events (card transactions) and more complex events (transactions of the legal entities) at the end of Section 4.3.

4.2.3 Fine-tuned embeddings. In the second scenario, we fine-tune pre-trained models for specific downstream tasks (see Figure 1, Phase 2b). The models are pre-trained using CoLES or another self-supervised learning approaches and then are trained on the labeled data for the specific end task.

The fine-tuning step is done by adding a classification network \( h \) (single-layer neural network with softmax activation) to the pre-trained encoder network \( M \) (see Section 3.4). Both networks are trained jointly on the downstream task, i.e., the classifier takes the output of the encoder and produces a prediction \( \hat{y} = h(M(x)) \) and its error propagates back through both. In addition to the aforementioned baselines, we compare our method to a supervised learning approach, where the encoder network \( M \) is not pre-trained using self-supervised target.

As Table 7 shows, CoLES representations obtained after fine-tuning achieve superior performance on all the considered datasets, outperforming other methods by significant margins.

4.2.4 Semi-supervised setup. Here we study the applicability of our method in scenarios where the amount of labeled examples is limited. We performed a series of experiments where only a random fraction of available labels is used to train the downstream task models. As in the case of the supervised setup, we compare the proposed method with hand-crafted features, CPC, and supervised learning without pre-training. The results are presented in Figure 4. Note that the performance improvement of CoLES in comparison to the supervised-only methods increases as we decrease the portion of labeled examples in the training dataset. Also note that CoLES consistently outperforms CPC for different volumes of labeled data.

4.3 CoLES Embeddings in Commercial Settings We applied the proposed self-supervised CoLES method to several machine learning tasks, routinely considered in a large European financial services company. In particular, two types embeddings were created: (1) legal entity embeddings of the small-and-medium-size companies, based on commercial transactions and operational histories of their businesses, and (2) individual embeddings of individual/retail customers, based on their debit/credit card transaction histories. Tables 8 and 9 provide examples of the transactional data used for building individuals’ and legal entities’ embeddings. Overall, the dataset of ten million corporate clients with on average 200 transactions per client was used to train the embeddings of type (1), and the dataset of five million individual clients with the mean number of 400 transactions per client was used to train the model for embeddings of type (2). These two “in-house” commercial datasets are considerably larger than the public datasets outlined in Section 4, and the extra volume of self-supervised training data allowed us to generate embeddings of significantly higher quality than on the publicly available data.

We performed extensive evaluation of CoLES embeddings on these in-house datasets by applying them to different downstream tasks. Legal entity embeddings were applied in the following use cases:

- Corporate medical insurance lead generation. In this task, the model should be able to predict client’s interest in a corporate medical insurance product.
Table 6: Quality of unsupervised embeddings as features for the downstream task

| Method            | Age Accuracy | Churn AUROC | Assess Accuracy | Retail Accuracy | Scoring AUROC |
|-------------------|--------------|-------------|-----------------|-----------------|---------------|
| Designed features | 0.631±0.003  | 0.825±0.004 | 0.602±0.005     | 0.547±0.001     | 0.779±0.001   |
| SOP               | 0.493±0.006  | 0.782±0.005 | 0.577±0.002     | 0.428±0.001     | 0.724±0.001   |
| NSP               | 0.622±0.004  | 0.830±0.004 | 0.581±0.003     | 0.425±0.002     | 0.760±0.001   |
| RTD               | 0.632±0.002  | 0.801±0.004 | 0.580±0.003     | 0.520±0.001     | 0.791±0.001   |
| CPC               | 0.594±0.002  | 0.802±0.003 | 0.588±0.002     | 0.525±0.001     | 0.791±0.001   |
| CoLES             | 0.638±0.007  | 0.843±0.003 | 0.601±0.002     | 0.539±0.001     | 0.792±0.001   |

average test set quality metric and its standard deviation for 5 runs on different folds is shown.

Table 7: Quality of the pre-trained model on the downstream tasks

| Method          | Age Accuracy | Churn AUROC | Assess Accuracy | Retail Accuracy |
|-----------------|--------------|-------------|-----------------|-----------------|
| Designed features | 0.631±0.003  | 0.825±0.004 | 0.602±0.005     | 0.547±0.001     |
| Supervised learning | 0.628±0.004  | 0.817±0.009 | 0.602±0.005     | 0.542±0.001     |
| RTD pre-train   | 0.635±0.006  | 0.819±0.005 | 0.586±0.003     | 0.544±0.002     |
| CPC pre-train   | 0.615±0.009  | 0.810±0.006 | 0.606±0.004     | 0.549±0.001     |
| CoLES pretrain  | 0.644±0.004  | 0.827±0.004 | 0.615±0.003     | 0.552±0.001     |

average test set quality metric and its standard deviation for 5 runs on different folds is shown.

Table 8: Data structure of the credit card transactions

| Date  | Amount | Currency | Country | Merchant       | Type  |
|-------|--------|----------|---------|----------------|-------|
| Jun 21| 230    | EUR      | France  | Restaurant     |       |
| Jun 21| 5      | USD      | US      | Transportation |       |
| Jun 22| 40     | USD      | US      | Household      | Appliance |

Table 9: Data structure of the money transfers between legal entities

| Date  | Amount | Currency | Sender      | Receiver     | Type  |
|-------|--------|----------|-------------|--------------|-------|
| Jul 11| 20000  | EUR      | 1232323     | 5424443      | 23    |
| Jul 11| 5000   | USD      | 1232323     | 5424443      | 12    |
| Jul 12| 14000  | USD      | 1232323     | 5424443      | 14    |

The information about company business and the company region is encoded in the first letters of the company identifier stored in "Sender" and "Receiver" fields.

- **Credit lead generation** for small and medium size businesses. In this task, the model should predict an interest of a company in taking a credit.
- **Credit scoring** for small and medium size businesses. In this task, the model should predict the the probability of a company’s default.
- **Holding structure restoration.** In this task, the model should predict if a pair of companies are in the same holding of companies.
- **Fraudulent money transfers monitoring.** In this task, the model is used to estimate the likelihood that a particular transaction is fraudulent.

As opposed to legal entities, individual embeddings are employed in following downstream tasks:
• **Retail credit scoring.** In this task, the model should estimate the probability of default when a client is taking a retail credit.

• **Customer churn prediction.** In this task, the model should predict the possibility that a client would stop using the company products (cards and deposit accounts).

• **Life insurance lead generation.** In this task, the model should predict an interest in a life insurance product.

We considered the following three scenarios in most of these tasks: (1) the baseline scenario – only the hand-crafted features were used; (2) the CoLES scenario – the produced self-supervised embeddings serve as features; (3) the hybrid (Baseline + CoLES) scenario, combining the hand-crafted features and CoLES embeddings. In all of these three scenarios, we used the LightGBM method [20] for modelling in the downstream task. In the first and the third scenarios, we deployed the sets of hand-crafted features, previously utilized in the organization (see Section 4.1.2 for examples of the used hand-crafted features).

The results of our experiments are presented in Tables 10 and 11. We observe that CoLES embeddings significantly improve upon the hand-crafted features in terms of the test performance on end task.

Note that it is more difficult to design valuable hand-crafted features for legal entities than for individual customers. A typical feature is some statistic aggregated over groups of transactions on some level. For example, one can aggregate card transactions of an individual customer on the level of their “merchant type” (MCC) field. In contrast, it is unclear how to group fund transfers of a company by the “receiver” field (see examples in Table 9). It is hard to manually find a perfect level of aggregation for receivers, since they can be grouped in many different ways, e.g. by region, size, the type of business, etc. We believe that CoLES is able to automatically learn a suitable aggregation level. This is one of the reasons why in our experiments the legal entity embeddings demonstrate higher relative improvements with respect to hand-crafted features than individual embeddings.

### 4.3.1 Deployment details

In production environments, our method is applied in two stages: training of the encoder neural net $A$ (the training part), followed by calculation of the embeddings with it (the inference part). We used only a part of the available data for training (10 million corporate clients, and 5 million individual clients), but applied the learnt embedder to all available transactional data, with more than 90 million cards in total. We did not use any of the available distributed training techniques [21, 29, 50] during the training part. During the inference state we leveraged horizontal scaling scheme, wherein different sequences are processed independently in parallel on different nodes of a Hadoop cluster.

In order to minimise the efforts of deploying CoLES embeddings inside the company, we used an ETL process for incremental re-calculation of embeddings upon arrival of new transactional data. Specifically, unlike transformers, recurrent encoders $\phi_{\text{enc}}$, such as GRU [6], reuse prior computations and enable incremental calculation: the embedding $c_{t+k}$ can be computed iteratively from $c_t$ and $(z_{t+j})_{j=1}^k$, using $c_{t+j} = \phi_{\text{enc}}(z_{t+j}, c_{t+j-1})$. This architectural choice reduces the inference time needed for updating the embeddings online.

### 5 CONCLUSIONS

In this paper, we present Contrastive Learning for Event Sequences (CoLES), a novel self-supervised method for building embeddings of discrete event sequences. CoLES can be efficiently used to produce embeddings of complex event sequences for various downstream tasks.

We empirically demonstrate that our approach achieves strong performance results on several downstream tasks and consistently outperforms both classical machine learning baselines on hand-crafted features, as well as on several existing self-supervised and semi-supervised learning baselines adapted to the domain of event sequences. In the semi-supervised setting, where the number of labeled data is limited, our method demonstrates confident performance: the lesser is the labeled data, the larger is the performance margin between CoLES and the supervised-only methods.

Finally, we demonstrate superior performance of CoLES in several production-level applications, internally used in our financial services company. The proposed method of generating embeddings appears to be useful in production environments since pre-calculated embeddings can be easily used for different downstream tasks.
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