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Interleaved Sequence RNNs for Fraud Detection

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Contribution

(1) We identify a new type of problem: a sequence composed of many interleaved, unbounded sub-sequences.

(2) We propose an efficient batch training technique, sorting per subsequence and time, processing scorable and nonscorable events.

(3) We introduce an efficient streaming inference technique, saving and restoring the GRU state, caching, and expiring events.

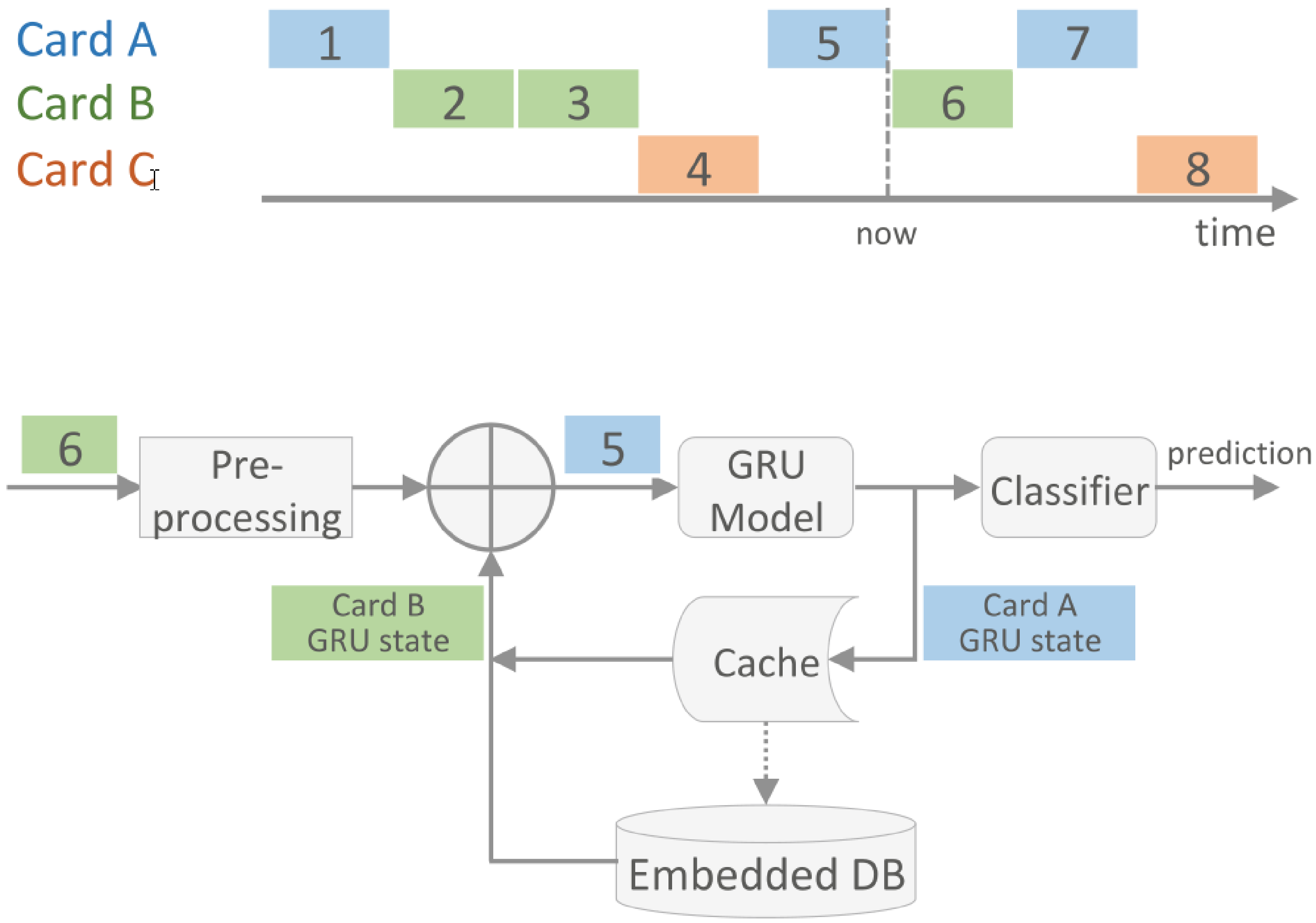
(4) We evaluate the solution in two real-life use.

Problem formulation

Each instance is an event denoted by a vector x labeled as fraudulent, y = 1, or legitimate, y = 0. More or less information can be added depending on the use-case; however, in general, we assume x to contain:

- N_n numerical fields x_{n_i}, i = 1 to N_n, containing at least the amount involved in the transaction, but also possibly other fields;
- N_c categorical fields x_{c_j}, j = 1 to N_c, usually strings, such as the merchant category code (MCC), the merchant's name, country code, currency code, or input mode of the card data;
- N_t timestamp fields x_{t_k}, k = 1 t o N_c, containing at least the timestamp of the transaction but also possibly including the expiry and issuing dates of the bank card;
- an entity identification field, usually a unique ID of the credit or debit card involved in the transaction, x_{id}.

Model architecture



Model architecture

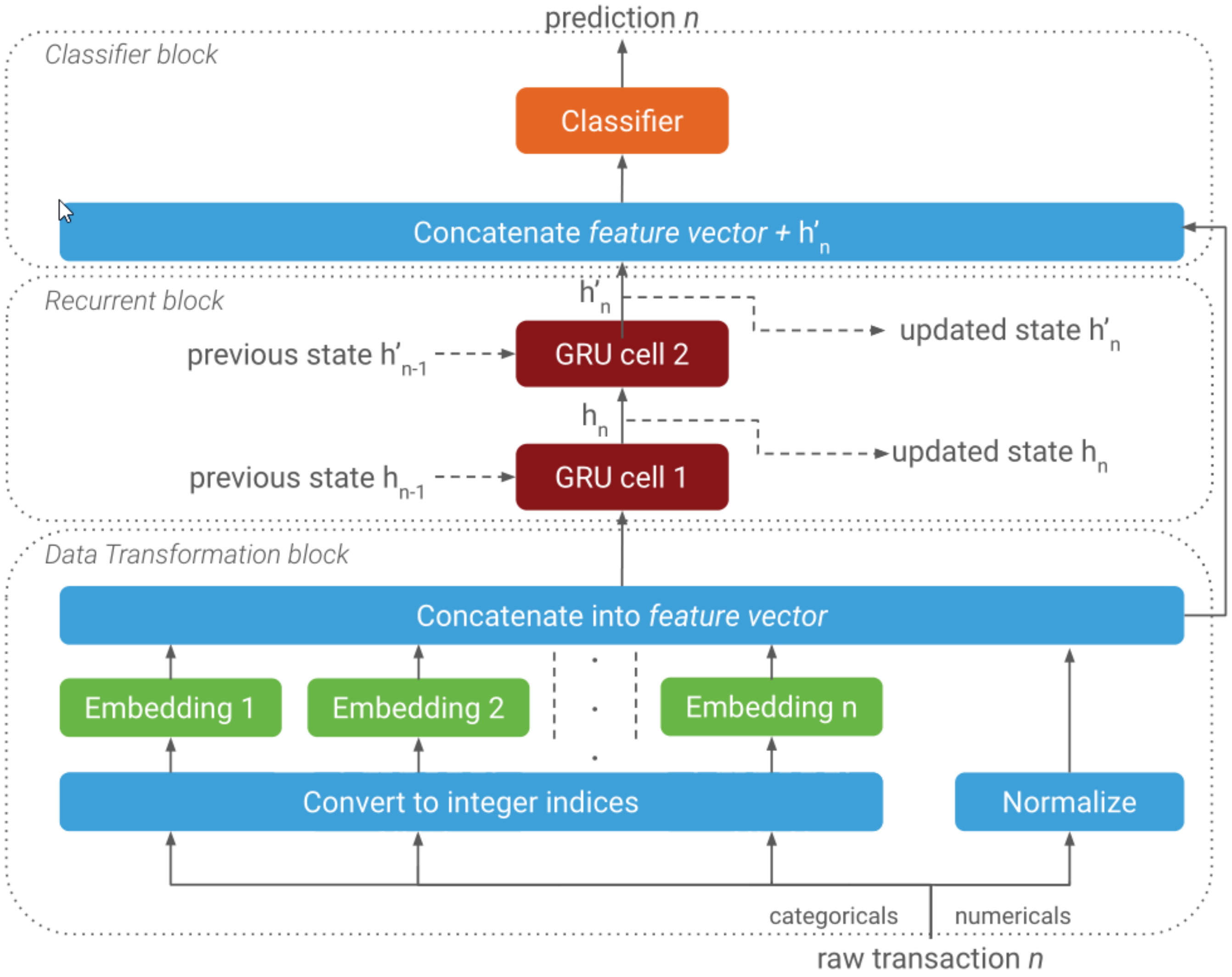
- we assume that a decision can depend on past events of an entity through a fixed-size state vector s for that entity that encodes information from past events as follows:

$$P\left(y^{(i,k)}\right) = P\left(y^{(i,k)} \middle| x^{(i,k)}, x^{(i-1,k)}, \dots, x^{(1,k)}\right)$$
$$= P(y^{(i,k)} | x^{(i,k)}, s^{(i,k)})$$

- We adopt the following recursive update of the state s(i,k)to compute the model prediction, $\hat{y}^{(i,k)}$:

$$x'^{(i,k)} = f\left(x^{(i,k)}\right)$$
$$s^{(i,k)} = g\left(s^{(i-1,k)}, x'^{(i,k)}\right)$$
$$\hat{y}^{(i,k)} = h(s^{(i,k)}, x'^{(i,k)})$$

Model architecture



Offline preprocessing

➢Numerical features

1、Z-score

2、Percentile bucketing for features with multimodal distributions

➢Categorical features

For a given categorical feature, x_{cj}, the l^{th} most frequent value is mapped to the integer$x'_{cj} = l - 1$. All values below a certain number of occurrences map to the same integer l_{max}. Missing values are considered a possible value.

Offline preprocessing

➢Timestamp features

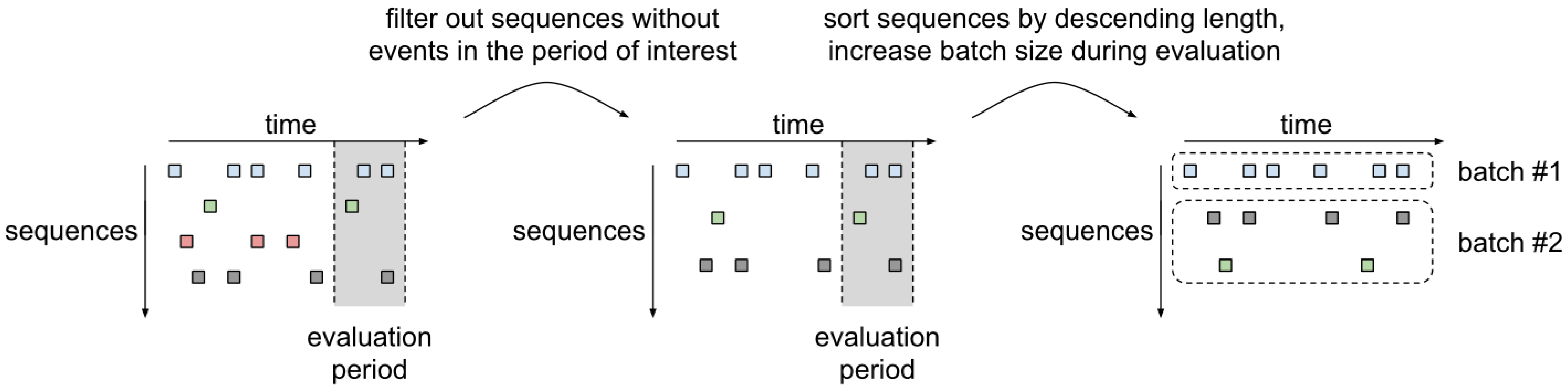
- hour-of-day features sin(h_k) and cos(h_k),
- day-of-week features sin(dw_k) and cos(dw_k),
- day-of-month features sin(dm_k) and cos(dm_k)

➢Entity-based features

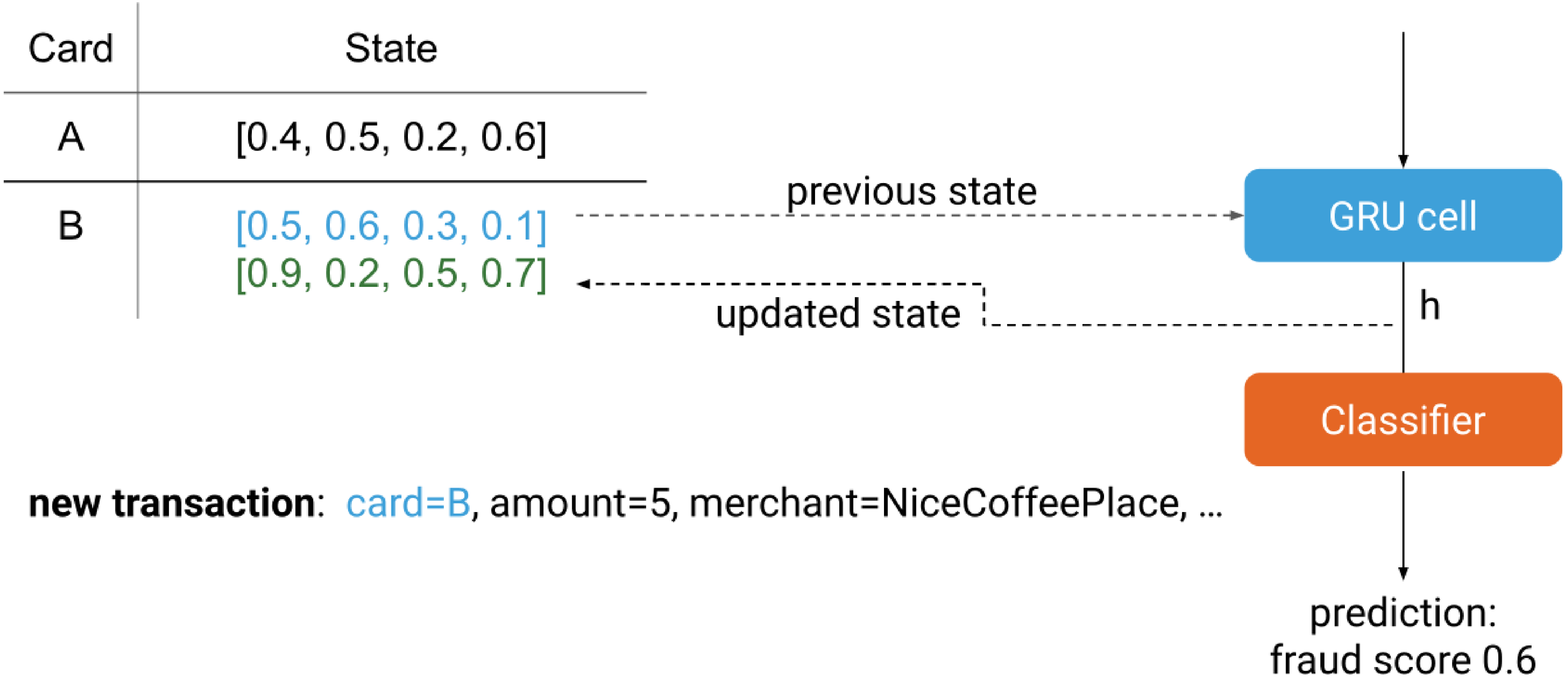
$$x_{\Delta t}^{*(i,k)} = x_t^{(i,k)} - x_t^{(i-1,k)}$$

This feature is especially important because of the irregular time intervals between events.

Offline preprocessing



Offline preprocessing



Dataset

Dataset	A	B
Total number of transactions	1B	4B
Total number of cards (entities) involved	76M	65M
Average number of transactions per card	7	61
Ratio of fraudulent to legitimate transactions	1:200	1:7000
Number of raw categorical features	15	53
Number of raw numerical features	2	4
Number of raw time-related features	2	2
Time period (months)	7	10

Results

Probe (ms)	mean	99%	99.9%	99.99%	99.999%
Write disk (async)	0.05	0.06	0.37	62.37	398.70
Read (cache or disk)	0.01	0.01	0.10	0.50	3.13
Total prediction time	4.06	10.47	42.82	75.90	126.66

Thanks