Meta-Sketch: A Neural Data Structure for Estimating Item Frequencies of Data Streams

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Abstract

To estimate item frequencies of data streams with limited space, sketches are widely used in real applications, including real-time web analytics, network monitoring, and self-driving. Sketches can be viewed as a model which maps the identifier of a stream item to the corresponding frequency domain. Starting from the premise, we envision a neural data structure, which we term the *meta-sketch*, to go beyond the basic structure of conventional sketches. The meta-sketch learns basic sketching abilities from meta-tasks constituted with synthetic datasets following *Zipf* distributions in the pre-training phase, and can be fast adapted to real (skewed) distributions in the adaption phase. Extensive experiments demonstrate the performance gains of the meta-sketch and offer insights into our proposals.

Introduction

Estimating item frequency is a basic topic in data stream processing, which finds applications in the fields of networking, databases, and machine learning, such as real-time data analyzing (Weller 2018; Zhu and Shasha 2002; Tinati et al. 2015; Irfan and Gordon 2019), network traffic monitoring (Huang, Lee, and Bao 2018; Madden and Franklin 2002; Wang et al. 2013), natural language processing (Goyal, III, and Cormode 2012) and search ranking (Dzogang et al. 2015). Towards infinite data streams, a common class of solutions (Cormode and Muthukrishnan 2005; Charikar, Chen, and Farach-Colton 2002; Estan and Varghese 2002; Roy, Khan, and Alonso 2016; Zhou et al. 2018; Hsu et al. 2019) use a compact structure taking sublinear space for counting the number of occurrences of each stream item, called the *sketch*.

Under the prevalent evidence of skewed distributions in data streams, *basic sketches* achieve the space compactness by hashing and approximately aggregating stream items. Basic sketches, including CM-sketch (Cormode and Muthukrishnan 2005), C-sketch (Charikar, Chen, and Farach-Colton 2002) and CU-sketch (Estan and Varghese 2002), use a 2D array of counters as the core structure. Some varients (Li et al. 2020; Zhong et al. 2021; Gao et al. 2022; Liu and Xie 2021) broaden application scenarios based on basic sketches. To optimize the sketching performance, several *augmented sketches* (Roy, Khan, and Alonso 2016; Zhou et al. 2018) were proposed, which attach filters to basic sketches, to capture the preliminary patterns of skewed distributions (e.g., high/low-frequency items). By separately maintaining the filtered high/low-frequency items, augmented sketches strive to eliminate the estimation error incurred by hash collisions between the high- and low-frequency items. Further, *learned augmented sketches* (Hsu et al. 2019) improve the filters of the augmented sketches by memorizing short-term high/low-frequency items via a pre-trained neural network (NN in short) classifier. But it is not clear how the pre-trained NN can be adapted to dynamic streaming scenarios, where the correspondence between items and frequencies varies. In a nutshell, sketches are structures compactly summarizing streams to count item frequencies with limited space budgets.

From the retrospective analysis, an observation can be drawn that the evolution of sketches conforms with the exploitation of data distributions. It is thus a natural evolution to consider a sketch that generally and automatically captures more distribution patterns with limited space budget. In this paper, we envision a novel neural sketch, called the *meta-sketch*, with techniques of meta-learning and memory-augmented neural networks. The meta-sketch learns the sketching abilities from automatically generated meta-tasks. Depending on the types of meta-tasks, we study two versions of the meta-sketch, called *basic* and *advanced meta-sketches*.

The basic meta-sketch implements the simulation of basic sketches, through the training process with basic meta-tasks following *Zipf* distributions, which are prevalent in the scenes of real data streams (Kolajo, Daramola, and Adebiyi 2019; Zeng and Li 2014; Babcock et al. 2002; Cormode et al. 2012; PhridviRaja and GuruRao 2016). The advanced meta-sketch extends the basic version to fast adapt to the specific runtime of stream processing, through the training with adaptive meta-tasks, which are generated by online sampling of real data streams. Our work follows a typical setting where the distribution of item frequencies follows a skewed distribution, but the correspondence between items and frequencies varies. For example, in software-defined networks (SDN), sketches are deployed to programmable switches to collect per-flow statistics, where IP packets follow *heavy-tailed* distributions (Tang, Huang, and Lee 2019; Hsu et al. 2019). In distributed databases, it gives advances to collect statistics of data shards to optimize data placement and query caching, where query phrases follow approximate *Zipf* dis-

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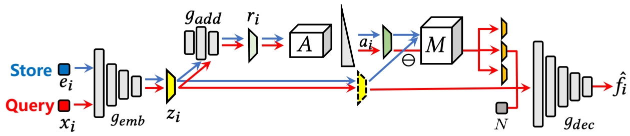


Figure 1: The Framework of the Meta-Sketch

tributions (Hsu et al. 2019). Given that the item population follows a specific distribution, the local distributions, i.e., item-frequency correspondences on shards or flows, are different. Instead of retraining learned augmented sketches on each local distribution, the advanced-sketch can be quickly adapted to different local distributions once trained.

As a member of the neural data structure family (Kraska et al. 2018; Rae, Bartunov, and Lillicrap 2019; Hsu et al. 2019; Mitzenmacher 2018), the meta-sketch significantly differs from conventional sketches, in terms of the structure and working mechanism. The meta-sketch utilizes NN's powerful encoding/decoding capabilities to perceive data distributions and express and compress explicit or implicit information to retrieve item frequencies with better accuracies. Meanwhile, the meta-sketch is differentiable to fully perceive frequency patterns for self-optimization.

Our contributions are as follows. **1)** We propose the meta-sketch, the first neural data structure for the problem of item frequency estimation, based on meta-learning. **2)** The basic meta-sketch acquires sketching abilities by learning from synthetic datasets and outperforms basic sketches in real datasets. The advanced meta-sketch automatically encompasses the ability analogous to the auxiliary structures deliberately devised in (learned) augmented sketches, yet yields better accuracies and robustness when adapted to dynamic scenes. **3)** Through extensive empirical studies on real and synthetic datasets, we evaluate our proposed meta-sketches and analyze the mechanism of major modules.

Meta-Sketch Structure

Preliminaries

We consider a standard data stream scenario (Cormode et al. 2012). Suppose a stream $\mathcal{S}_N : \{e_1, ..., e_N\}$ with N items and n distinct items. Each item $e_i \in \mathcal{S}_N$ takes a value from the item domain $\mathbb{X} = \{x_1, ..., x_n\}$ where $x_i \neq x_j$. The frequency f_i is equal to the number of times that item x_i appears in $\mathcal{S}_N$.

To leverage learning techniques for item frequency estimation, a naïve way is to train a NN model (e.g., MLP/LSTM) that learns/memorizes the mapping relationship between items and frequencies with multiple training iterations, similar to (Kraska et al. 2018; Hsu et al. 2019; Mitzenmacher 2018). However, it violates the typical setting of stream processing where item observations are transient and are therefore handled in one pass (Babcock et al. 2002). More, the costly procedure has to be repeated from the scratch for a new data stream. Inspired by the meta-bloom filter (Rae, Bartunov, and Lillicrap 2019), we consider a case of one-shot learning (fitting for one-pass stream processing) by using meta-learning (Hospedales et al. 2020; Santoro et al. 2016) and memory-augmented networks (Graves, Wayne, and Danihelka 2014; Graves et al. 2016). Meta-learning employs sampled meta-tasks to learn the ability to solve a class of domain tasks rather than memorizing patterns for a specific task. The memory-augmented networks incorporate external memories into NN models, significantly enhancing the potentials of NN models with more learnable parameters. Meanwhile, it performs efficient and explicit operations (i.e., reading and writing) for external memories, allowing NN models to process information similarly to conventional data structures.

The framework of the meta-sketch consists of 4 functional modules, *Embedding* ($\mathcal{F}_E$), *Sparse addressing* ($\mathcal{F}_{Sa}$), *Compressed storage* matrix (M), and *Decoding* ($\mathcal{F}_{dec}$), as shown in Figure 1. Like traditional sketches, the meta-sketch encodes and memorizes online stream items in one pass, and answers queries by decoding corresponding item-frequency information from the structure.

Thus, we define 2 operations, *Store* and *Query*. Specifically, the *Store* operation first passes each incoming stream item to $\mathcal{F}_E$ for the embedding representation, and then writes the embedding vector into M, according to the address derived by $\mathcal{F}_{Sa}$. When estimating the frequency of an item, the *Query* operation calculates the item's address in M via $\mathcal{F}_{Sa}$, reads the corresponding information vector from M and decodes the frequency by $\mathcal{F}_{dec}$ from the retrieved information vector.

Modules

Embedding. The module $\mathcal{F}_E$ has two purposes: **1)** performing representational transformation for an incoming item e_i and mapping it into a dense embedding vector z_i that holds implicit features about item-frequency distributions and serves as the basis for identifying stream items; **2)** decoupling the embedding vector z_i to obtain a refined vector r_i, which is used to derive the address for reading/writing on the compressed storage matrix M.

Accordingly, $\mathcal{F}_E$ consists of the embedding network g_{emb} and the address network g_{add}. We assume that an item $e_i \in \mathcal{S}_N$ is numerically encoded for the unique identification, following the conventions of stream processing (Babcock et al. 2002; Cormode et al. 2012). Thus, we have $z_i, r_i \leftarrow \mathcal{F}_E(e_i)$, where $z_i \leftarrow g_{emb}(e_i)$ and $r_i \leftarrow g_{add}(z_i)$. Here, $z_i \in \mathbb{R}^{l_z}$ is an embedding vector of dimension l_z, and $r_i \in \mathbb{R}^{l_r}$ is a refined vector of dimension l_r. The vector z_i serves multiple intents: **1)** it makes a basis for deriving the address of an item in $\mathcal{F}_{Sa}$; **2)** it serves as the compressed vector of an item written into M; **3)** it works as a partial input of $\mathcal{F}_{dec}$ for decoding the item frequency; **4)** it also plays the role of perceiving/compressing patterns of a specific frequency distribution, as discussed in analysis section. In addition, to enhance the addressing functionality and eliminate other interference factors, we decouple z_i to generate a refined vector r_i, instead of using z_i directly for the addressing.

Sparse Addressing. The module $\mathcal{F}_{Sa}$ aims to derive the address a_i for storing the embedding vector z_i into the storage matrix: $a_i \leftarrow \mathcal{F}_{Sa}(r_i)$. In terms of functionality, $\mathcal{F}_{Sa}$ is analogous to the hash functions of traditional sketches, except that $\mathcal{F}_{Sa}$ is parameterized and differentiable. Specifically, the addressing of the meta-sketch is done via a 3D addressing matrix A of parameters to be learned and a sparse SoftMax function: $a_i \leftarrow SparseMax(r_i^T A)$, where $A \in \mathbb{R}^{d_1 \times l_r \times d_2}$.

Then, the batch matrix multiplication of A and the transpose of r_i results in the addressing vector $a_i \in \mathbb{R}^{d_1 \times 1 \times d_2}$.

The setting of d_1 and d_2 determines the size of address space for storing the embedding vectors. Typical addressing methods (Rae, Bartunov, and Lillicrap 2019; Graves et al. 2016) use a 2D matrix ($l_r \times d_2$) for recording the mapping of an embedding vector to a slot (d_2 is the number of slots). In contrast, we add one more dimension d_1 to simulate the multi-hash setting of traditional sketches, in view of that a 2D addressing matrix can reach a differentiable simulation of a hash function (Rae, Bartunov, and Lillicrap 2019; Mitzenmacher 2018). Matrix A simulates multiple hash functions, yielding robust frequency decoding and the rationality of the learning optimization. Note that each 2D slice A^* of A is stacked from d_2-unit vectors $b_i \in \mathbb{R}^{l_r}$ by normalizing the parameters of A at each gradient update of the training process. Normalized A can avoid overflowing when compressing its size by reducing data precisions and enhancing the interpretability (see analysis section).

In addition, we utilize sparse SoftMax (Martins and Astudillo 2016; Laha et al. 2018) instead of SoftMax to normalize the address a_i. It brings the following benefits by constraining some bits of a_i to zero, which **1)** promotes quick derivation during the back-propagation; **2)** reduces the overhead of storage matrix accessing by skipping the slots of M corresponding to the "0" bits of a_i; **3)** leads to de-noising with the vector compression.

Compressed Storage Matrix. We use a matrix $M \in \mathbb{R}^{d_1 \times l_z \times d_2}$ [1] to store an embedding vector $z_i \in \mathbb{R}^{l_z}$ in accordance to its address $a_i \in \mathbb{R}^{d_1 \times 1 \times d_2}$. The functionality of M is similar to the 2D array of counters in traditional sketches, yet yields better storage compression. Traditional sketches store item counts. Differently, M stores embedding vectors, which have richer information compression capabilities, due to the diversity of value change on different bits.

Decoding. Given a query item x_i, the module $\mathcal{F}_{dec}$, consisting of one NN component g_{dec}, decodes the information corresponding to x_i, to obtain the estimated frequency $\hat{f}_i$. The vector fed into g_{dec} is the concatenation of vector $\{M \ominus a_i\}$, vector z_i, and the current number of items (i.e., N) recorded in a counter, $\hat{f}_i \leftarrow g_{dec}(\{M \ominus a_i\}, z_i, N)$. The operator $\ominus$ refers to the reading operation for the storage matrix. The basic form of $\ominus$ gives the operation as $M \ominus a_i = M a_i^{T}$ [2] (Graves, Wayne, and Danihelka 2014; Graves et al. 2016). We consider two optimized forms of $\ominus$, inspired by the "count-min" mechanism of the CM-sketch. The first one gives the minimum value of each row in $M a_i^T$, aiming to remove the noise of other items. The second one gives the minimum value of each row in $M a_i^T \circ \frac{1}{z_i}$, a normalized form of $M a_i^T$. Here, $\circ$ denotes the Hadamard product, and z_i requires broadcast operations to comply with its requirements. So, $\{M \ominus a_i\}$ refers to the concatenation of vectors generated by the basic form and the two optimized forms.

Operations

Operation Store is performed by feeding an incoming item e_i to $\mathcal{F}_E$ and $\mathcal{F}_{Sa}$ to obtain embedding vector z_i and address a_i, and then additively writing z_i to M, weighted by a_i: $M \leftarrow M + z_i a_i$. Here, other writing types (Graves, Wayne, and Danihelka 2014; Graves et al. 2016; Rae, Bartunov, and Lillicrap 2019; Santoro et al. 2016) can also be employed, but simple additive writing is more efficient and allows to compute gradients in parallel (Rae, Bartunov, and Lillicrap 2019). In addition, additive writing also allows to define $Delete$ operation for meta-sketch (see the supplement materials[3]).

Operation Query estimates the frequency of a given query item x_i. First, z_i and a_i are obtained, similar to that of operation Store. Then, the vectors $\{M \ominus a_i\}$ are retrieved from M and N can be easily obtained by a small counter. Finally, $\{M \ominus a_i\}$, z_i and N are jointly fed into g_{dec} to get the estimated frequency $\hat{f}_i$ of x_i as the returned value. The two operations are shown in Algorithm 1.

Algorithm 1: Operations

Operation `Store(`e_i, M`)`**:**
    $z_i, r_i \leftarrow \mathcal{F}_E(e_i)$; $a_i \leftarrow \mathcal{F}_{Sa}(r_i)$; $M \leftarrow M + z_i a_i$;
Operation `Query(`x_i,M,N`)`**:**
    $z_i, r_i \leftarrow \mathcal{F}_E(x_i)$; $a_i \leftarrow \mathcal{F}_{Sa}(r_i)$;
    return $\hat{f}_i \leftarrow \mathcal{F}_{dec}(\{M \ominus a_i\}, z_i, N)$;

Algorithm 2: Training Framework

Data: Learnable parameters θ of Meta-Sketch, Sampler R;
while *i not reach max training steps* **do**
    Sample a meta-task $t_i : \{s_i, q_i\} \sim R$ and count N;
    for $e_j^{(i)} \in s_i$ **do** `Store(`$e_j^{(i)}$, M`)`; **end**
    for $x_j^{(i)}, f_j^{(i)} \in q_i$ **do** $\hat{f}_j^{(i)} \leftarrow$ `Query(`$x_j^{(i)}$, M,N`)`;
    $\mathcal{L}$+=LossFun($f_j^{(i)}, \hat{f}_j^{(i)}$);
    Backprop through: $d\mathcal{L}/d\theta$ and update parameters θ
    Normalize A and Clear M;
end

Meta-Sketch Training

Training Framework

The meta-sketch employs an efficient one-shot meta-training method (Vinyals et al. 2016). The training process thus contains two phases, *pre-training* and *adaption* phases. In the pre-training phase, the meta-sketch learns an initial set of module parameters, including g_{emb}, g_{add}, A, and g_{dec}. The pre-training goes offline across training units, i.e., basic meta-tasks, to acquire the ability of stream frequency estimation. Then, in the adaption phase, the pre-trained meta-sketch goes fast across a set of light-weighted training units, i.e., adaptive meta-tasks, to quickly acquire the task-specific knowledge.

The training units, i.e., meta-tasks, are crucial for both phases. The training process of the meta-sketch on a single meta-task is equivalent to simulating storing and querying a data stream instance while computing the error to optimize the learnable parameters. Thus, a meta-task t_i consists of a store set s_i (also called a support set) and

[1] In this paper, we control $l_r : l_z \approx 1 : 5$ to compress A.

[2] a_i^T means transpose operation for dim 1 and d_2

[3] https://github.com/FFY0/meta-sketch/blob/main/Sup_ms.pdf

a query set q_i. The store set s_i can be viewed as an instance of data streams, s_i:$\{e_1^{(i)}, ..., e_{N_i}^{(i)}\}$, where N_i is the number of stream items. The query set q_i can be represented by a set of items with paired frequencies in s_i, formally, q_i:$\{(x_1^{(i)}:f_1^{(i)}), ..., (x_{n_i}^{(i)}:f_{n_i}^{(i)})\}$, where n_i is the number of distinct items in s_i. In this work, we define two types of meta-tasks, *basic* and *adaptive* meta-tasks, corresponding to the pre-training and adaption phases, respectively.

The two training phases, that are based on different types of meta-tasks, follow the same training framework, as shown in Algorithm 2, except for the sampler and initial parameters. To reduce both absolute and relative errors,i.e.AAE and ARE,[4], we devise an adaptive hybrid loss function (Kendall, Gal, and Cipolla 2018) for the meta-sketch: $\frac{1}{2\sigma_1^2}(f_i - \hat{f}_i)^2 + \frac{1}{2\sigma_2^2}|f_i - \hat{f}_i|/f_i + log\sigma_1\sigma_2$, where σ_1 and σ_2 are learned parameters.

Basic Meta-Task Generation

In the pre-training phase, basic meta-tasks should make the meta-sketch to simulate traditional sketches and preserve certain generality without relying too much on the patterns of specific distributions. Therefore, we generate meta-tasks based on the Zipf distribution, which is found to be prevalent in real scenes of data streams (Kolajo, Daramola, and Adebiyi 2019; Zeng and Li 2014; Babcock et al. 2002; Cormode et al. 2012; PhridviRaja and GuruRao 2016). A meta-task is essentially a data stream instance with item size n, which can be determined by the total number of items N and the relative frequency distribution p. We can generate meta-tasks by presupposing different n, $\bar{f}$ and p, where $\bar{f}$ is the frequency mean, since N=$\bar{f}\times n$. Thus, basic meta-task generation is based on a sampler $R : \{I, L, P\}$, as follows.

An **item pool** I is a subset of item domain $\mathbb{X}$. If the item domain is known a-priori, it can be directly taken as the item pool. Otherwise, if the item domain is only partially known or even unknown, the item pool can be constructed by sampling from historical records. Even if the item pool does not completely cover the item domain, the “missing” item can still be identified, due to the homogeneity of the domain-specific embedding space, given that the number of distinct items is less than the item pool capacity $|I|$.

A **frequency mean range** L is the range for the frequency mean $\bar{f}$. One can get the value of $\bar{f}$ by statistics of sampled stream instances and extract the min and max $\bar{f}$s to build L.

A **distribution pool** P consists of many instances generated according to different parameters of relative frequency distributions. In this paper, we consider a family of *Zipf* distributions (Adamic 2000) with varied parameter α, as the base for constructing P. α can be selected from a wide range to have a good coverage of different distributions.

Notice that the meta-tasks are for the meta-sketch to learn the sketching ability, instead of spoon-feeding the meta-sketch to mechanically memorize the parameters of R. It means that the trained meta-sketch has the generalization ability to handle the case not covered in R. The generation of a meta-task t_i can be done based on sampler R, as follows.

[4] $AAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - \hat{f}_i|$; $ARE = \frac{1}{n}\sum_{i=1}^{n}\frac{|f_i - \hat{f}_i|}{f_i}$.

We first randomly sample a subset of n_i items from I, and a frequency mean $\bar{f}_i \in L$. Then, we sample a distribution instance $p_i \in P$ and make the n_i items' frequencies conform to p_i and $\bar{f}_i$. For example, the frequencies of n_i items can be set as $n_i \times \bar{f}_i \times p_i$, where $p_i \sim Zipf(\alpha)$ is a random variable. The above steps are repeated until the s_i and q_i are built.

Adaptive Meta-Task Generation

While processing real data streams, we can get the item set I_r and its distribution p_r by online sampling. I_r and p_r are then used for generating the set of adaptive meta-tasks. For each adaptive meta-task, an item subset is sampled from I_r, and the relative frequency corresponding to each item is sampled from p_r. The process is similar to the generation of basic meta-tasks. The only difference from basic meta-task generation is that there is no distribution pool anymore because the real data stream is unique. Also, we intentionally randomize the correspondence between an item and its real relative frequency on the original data records. It is equivalent to constructing meta-tasks where the item frequencies dynamically change. For example, the frequency of an item may first increase, then suddenly drop (Tang, Huang, and Lee 2019). With adaptive meta-tasks, the meta-sketch learns to quickly adapt to the distribution p_r, while being flexible against the item frequency change. The detailed algorithms of generating meta-tasks are shown in supplement materials[3].

Experiments

Basic Setup

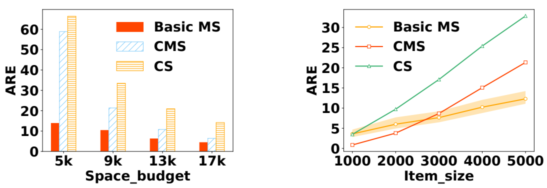
Dataset. For fair comparison with all competitors, we choose two widely used real datasets in data stream field. *Word-query (Wq)* is a streaming records of search queries, where each query contains multiple words (e.g., “News today”) (Hsu et al. 2019). *IP-trace (It)* consists of IP packets, where each packet is identified by a unique IP address pair (e.g., 192.168.1.1/12.13.41.4) (Tang, Huang, and Lee 2019). IP-trace follows heavy-tailed distributions and the Word-query follows Zipfian distributions. All items in the two datasets are numerically encoded, similar to (Hsu et al. 2019).

Baseline. We hereby evaluate the basic and advanced meta-sketches (BMS and AMS). CM-sketch (CMS) and C-sketch (CS) are the basis for other sketch variants and the commonly accepted baselines. So we choose them as competitors to basic MS (after the pre-training phase). We compare the advanced MS (after the adaptation phase) with two variants of CM/C sketches, learned augmented sketch (LS) and cold filter (CF), which leverage auxiliary structures and both are the state-of-the-art in their own category. According to the default setting (Cormode and Muthukrishnan 2005; Charikar, Chen, and Farach-Colton 2002), the number of hash functions for all sketches is 3. We adopt two standard metrics for evaluating the accuracies of frequency estimation, AAE and ARE[4].

Parameters. We implement g_{emb} or g_{add} in MLP with 2-layers of sizes 128 and 48, followed by batch normalization, and g_{dec} in a MLP with 3-layers of 256 with residual connections. We use the $relu$ function for layer connections. The space budget B is spent on storing M, the same as the setting in neural data structures (Rae, Bartunov, and Lillicrap

n B		5K 9KB	10K 11KB	20K 13KB	40K 15KB
BMS	ARE	**12.30**	**14.74**	**10.98**	**13.79**
(Wq)	AAE	**31.54**	**38.54**	**40.63**	**53.67**
CS	ARE	32.94	57.97	98.01	162.43
(Wq)	AAE	57.54	101.44	172.44	282.59
CMS	ARE	21.34	48.33	111.82	239.11
(Wq)	AAE	38.04	84.62	195.61	416.01
BMS	ARE	**3.00**	**1.51**	**2.97**	**1.13**
(It)	AAE	**5.57**	**5.01**	**6.94**	**5.56**
CS	ARE	6.08	9.94	15.57	24.49
(It)	AAE	10.42	16.82	26.46	41.91
CMS	ARE	8.12	16.07	32.77	65.19
(It)	AAE	13.67	27.39	55.29	110.65

Table 1: Results of Basic Meta-Sketch (T_r)



(a) ARE w.r.t. B (b) ARE w.r.t. n

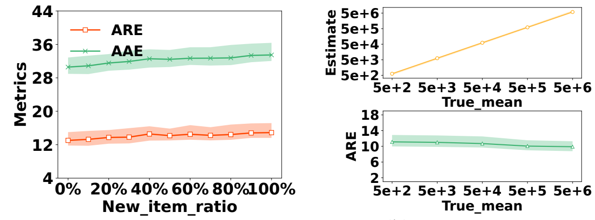
Figure 2: Basic Meta-Sketch w.r.t. Space Budget/Item Size

2019). Other modules, like hashing libraries, are commonly accepted as reusable and amortizable resources for multi-deployment of sketches (Rae, Bartunov, and Lillicrap 2019; Tang, Huang, and Lee 2019). Note that due to space limitations, the details and methods of parameter settings of $M(A)$, the ablation experiments and some parameter discussions are shown in the supplement materials[3].

Basic Meta-Sketch

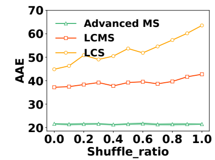
Settings. For each dataset, we train the basic MSs under 4 item pools with $\{5K, 10K, 20K, 40K\}$ different items, respectively. The meta-task samplers are with *Zipf* distributions. We build the distribution pools set with $\alpha \in [0.8, 1.3]$ and set frequency mean range $L = [50, 500]$. For basic meta-sketch training, the default maximum number of training steps ϕ is 5 million, the learning rate is 0.0001, and the $Adam$ optimizer is used. For evaluation, we consider two types of tasks, T_r and T_s. T_r are directly obtained by random sampling on two real data streams with different values of n, i.e., the number of distinct items. Note that frequency distributions of T_r are not necessarily obey *Zipf* distributions. T_s are the synthetic tasks, where the frequency follows the *Zipf* distribution with $\alpha \in \{0.5, 1.1, 1.5\}$. To evaluate the generability and stability of basic MS, both $T_s(0.5)$ and $T_s(1.5)$'s distributions are not covered by the distribution pool of the meta-task samplers.

Performance. Table 1 shows the performance of all competitors based on real dataset T_r. It shows that the basic MS outperforms traditional basic sketches, i.e., CMS and CS, on all testing cases. For example, the results on IP-trace show that, when n=40K, B=15KB, the ARE of basic MS is 1.13, while AREs of CMS and CS are 65.19 and 24.49, respectively. The advantage of meta-sketch is significant when testing on T_s with different αs, as shown in Table 2. Note that we use random choices to simulate the ideal hash functions for traditional sketches (Hsu et al. 2019), so that CS and CMS have the same result with the same α in both datasets.



(a) New Items (b) New Means

Figure 3: Generalization



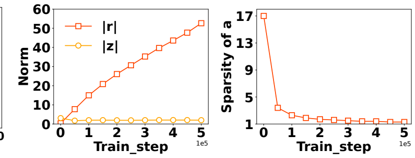


Figure 4: LS/MS Figure 5: $|r|$, $|z|$ w.r.t. Sparsity of a

We show the trend of ARE w.r.t. the space budget, in Figure 2 (a) (T_r, n=5K, Wq). Compared to the dramatic performance degrading of traditional sketches, basic MS holds stable performance. We show that the trend of ARE w.r.t. the number of distinct items in Figure 2 (b) (T_r, B=9KB, Wq). Compared to traditional sketches, the ARE of basic MS increases sub-linearly w.r.t. the value of n. The AAE has similar results, see the supplement materials[3].

Generalization. We test the generality of basic MS to new items that are not in the item pool of the meta-task sampler in Figure 3 (a). We make the experiments (n=5K, B=9KB, Wq) by replacing some items in T_r with new items, and vary the fraction of new items to observe the trend of the performance. It shows that the ARE/AAE moderately increases w.r.t. the ratio of new items. The performance is acceptable considering the fact that the item domain is often stable in practical applications. We then test the generality of meta-sketches to varied frequency means that are not in range L of the meta-task sampler, as shown in Figure 3 (b). The experiment (n=5K, B=9KB, Wq) is done by sampling a series of T_s tasks with frequency means in $\{500, 5K, 50K, 500K, 5000K\}$. It shows that as the mean of the true frequencies increases, the estimated frequencies of meta-sketch increase linearly, so that the ARE keeps stable.

Advanced Meta-Sketch

Settings. The generation of adaptive meta-tasks is similar to that of basic meta-tasks, except that each item pool reads real frequency distributions for the adaption as described in the adaptive meta-task generation section. In the adaption phase, the maximum number of training steps is $0.002 * \phi$.

Performance. Table 3 compares the performance of advanced MS with traditional sketches and their variants, LS and CF, on real dataset T_r. We implement two LSs according to (Hsu et al. 2019), learned CM-sketch (LCMS) and learned C-sketch (LCS), following the default setting that (top 1%) high-frequency items are separately stored. For CF, we follow the parameter setting in (Zhou et al. 2018), and use CF40, CF70, and CF90 for setting the filter percentages to

		n=5K B=9KB			n=10K B=11KB			n=20K B=13KB			n=40K B=15KB		
		0.5	1.1	1.5	0.5	1.1	1.5	0.5	1.1	1.5	0.5	1.1	1.5
BMS	ARE	**0.43**	**1.05**	**2.63**	**0.73**	**3.25**	**3.14**	**0.47**	**1.67**	**1.35**	**0.43**	**2.58**	**9.65**
(Wq)	AAE	**24.70**	**17.72**	**8.93**	**31.24**	**27.02**	**9.41**	**27.29**	**22.19**	**9.20**	**25.04**	**26.95**	**19.87**
BMS	ARE	**0.59**	**2.27**	**9.38**	**0.73**	**0.86**	**1.02**	**0.72**	**1.73**	**7.52**	**0.73**	**0.79**	**2.33**
(It)	AAE	**26.45**	**21.49**	**14.73**	**38.33**	**19.32**	**7.95**	**35.48**	**22.28**	**15.74**	**39.57**	**21.75**	**14.06**
CS	ARE	1.98	6.72	10.99	2.70	12.12	16.90	3.73	20.80	27.46	5.17	37.96	43.76
	AAE	74.96	47.98	15.89	102.05	75.83	23.80	140.65	118.29	38.70	194.32	198.40	59.96
CMS	ARE	4.96	7.52	5.47	9.27	15.85	9.44	17.29	32.70	16.38	32.24	66.35	27.89
	AAE	187.52	53.81	8.17	350.08	99.82	13.58	651.63	185.54	22.88	1213.38	347.32	38.18

Table 2: Results of Basic Meta-Sketch (T_s)

n		5K	10K	20K	40K
B		9KB	11KB	13KB	15KB
AMS	ARE	**3.05**	**2.83**	**4.06**	**5.20**
(Wq)	AAE	21.42	**26.11**	**35.00**	**43.81**
CF 90	ARE	3.58	14.53	141.70	1127.11
(Wq)	AAE	**21.13**	59.18	381.63	2217.28
CF 70	ARE	7.95	29.02	139.87	541.37
(Wq)	AAE	29.02	76.58	295.63	970.94
CF 40	ARE	91.16	138.64	244.24	407.83
(Wq)	AAE	174.86	252.22	421.85	693.47
LCMS	ARE	20.52	48.69	111.85	266.50
(Wq)	AAE	37.80	81.93	194.15	451.28
LCS	ARE	25.53	40.84	67.21	104.54
(Wq)	AAE	44.53	78.17	122.57	180.56
AMS	ARE	0.87	**0.89**	**1.38**	**2.29**
(It)	AAE	3.77	4.46	**5.13**	**6.55**
CF 90	ARE	**0.85**	2.74	4.20	16.71
(It)	AAE	**1.32**	**3.01**	7.71	31.20
CF 70	ARE	1.51	3.10	8.95	46.79
(It)	AAE	2.57	5.51	16.83	82.84
CF 40	ARE	12.62	33.50	103.76	155.61
(It)	AAE	24.16	60.79	175.14	279.72
LCMS	ARE	8.34	17.09	35.22	77.79
(It)	AAE	13.72	28.39	59.10	129.86
LCS	ARE	5.20	7.80	11.33	17.12
(It)	AAE	8.78	13.10	18.97	28.38

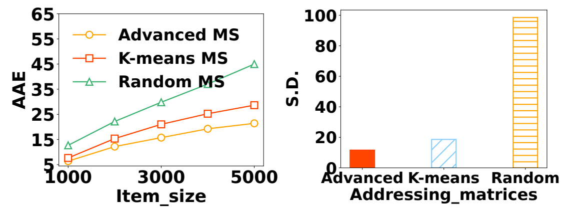
Table 3: Results of Advanced Meta-Sketch

40%, 70%, and 90%, respectively. It shows that the advanced MS achieves a better performance than LSs and CFs. Also, AAE/ARE of advanced MS increases more moderately w.r.t. the number of distinct items n, compared to its competitors.

Next, we compare the performance of the advanced MS and the LS under dynamic streaming scenarios, as shown in Figure 4. We select a set of T_r (n=5K, B=9KB, Wq), and gradually shuffle the correspondence between items and frequencies. It shows that the AAE of advanced MS only slightly fluctuates between 21.28 and 21.68. In contrast, AAEs of LCS/LCMS starts above 37, and increase significantly w.r.t. the increase of the shuffle ratio. Actually, the classifier of LS tends to incur more errors due to the gradual shift of high-/low-frequency items, resulting in an increased number of hash collisions, thus deteriorating the estimation accuracy.

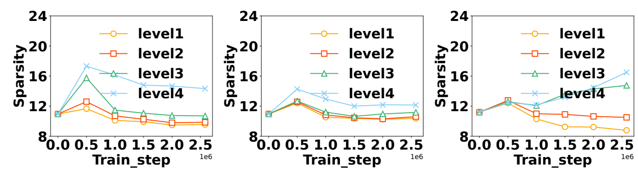
Analysis

The meta-sketch is trained based on meta-tasks, consisting of various stream distributions. We expected that meta-sketch can learn the ability to sketch item frequencies. Somehow, it is unavoidable that meta-sketch's ability is limited by patterns



(a) AAE (b) Standard Deviations

Figure 6: Three Addressing Matrices



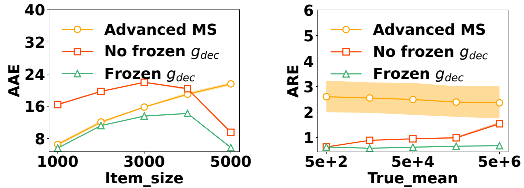
(a) Zipf (b) Triangular (c) Uniform

Figure 7: The Sparsity of Embedding Vectors

of given meta-tasks. Thus, the two training phases benefit the balance of the trade-offs. In pre-training, we select representative *Zipf* distributions for basic meta-tasks, making the meta-sketch adaptable to a wide range of data streams. In adaptation, we sample meta-tasks from raw data streams to make the meta-sketch more specialized. Next, we analyze the working mechanism of the modules of the meta-sketch as well as their roles in acquiring the two abilities.

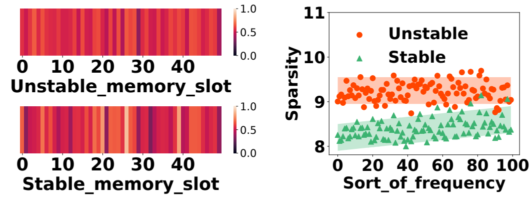
Sparse Addressing. We take a 2D slice A^* (size is $l_r \times d_2$) of the A to analyze the process of a refined vector r getting addressing a. Since A^* is formed by stacking unit vectors b_i, we have $SparseMax(r^T A^*)$=$SparseMax(|r|c)$. Here, c=$(cos\theta_1, ..., cos\theta_{d_2})$ and θ_i is the angle between r and b_i. We then continue to transform the form to obtain addressing $a \leftarrow Sparsegen(c; u; \frac{|r|-1}{|r|})$ as described in (Laha et al. 2018), where u is a component-wise transformation function applied on c, and we set $u(c)$=c.

Based on the principle of $Sparsegen$ (Laha et al. 2018), $|r|$ mainly affects the sparsity (i.e., the proportion of non-zero bits in the vector) of a, while c determines the positions and values of non-sparse bits. The Figure 5 shows a strong correlation between the average $|r|$ and the sparsity of a during training from scratch (n=5K, B=9KB, Wq, BMS). Since the embedding vector z does not directly participate in the addressing process, the average $|z|$ remains stable. Further, we observe that the sparsity of a will eventually converge to around 1, which means that each item is generally stored in a slot corresponding to the refined vector r and the unit vector in A^* with the maximum cosine similarity.



(a) Item Size (b) Frequency Mean

Figure 8: Generality w.r.t. Decoding



(a) Multiple Slots (b) A Single Slot

Figure 9: Unstable Case vs. Stable Case

Thus, the role of A^* is to map refined vectors to the addressing vectors. The d_2 unit vectors in A^* are the reference standard for mapping, which is equivalent to the mutually exclusive d_2 -divisions of the refined vector space. Follow this point, we build two matrices K^* and R^* of the same size as A^*. The d_2 unit vectors in K^* come from the cluster centers of the sampled refined vectors. To achieve mutually exclusive division, we perform *K-means* clustering with $K{=}d_2$ and *Cosine similarity* criterion. Then, we normalize the resulting d_2 cluster centers and stack them as K^*. In contrast, the unit vectors in R^* are entirely randomly generated.

Figure 6 (a) shows the results of replacing A^* on the trained meta-sketch with K^* and R^*. The meta-sketch with R^* shows the worst performance, but the performance of meta-sketch with K^* is close to original A^*. Furthermore, we count the number of items mapped in every slot of A^*, K^*, R^* and show their standard deviation in Figure 6 (b). The standard deviation of R^* is much higher than A^* and K^*, and a better meta-sketch tends to store items more evenly in each slot. Thus, the addressing module simulates the traditional sketch mechanism. Its principal function is to store the embedding vectors of items as evenly as possible in multiple memory slots, and an item is written to only one slot.

Embedding. The major source of conflicts in the meta-sketch is the stacking of different embedding vectors in a single slot. Thus, the sparsity of the embedding vector becomes an important indicator to determine the degree of conflicts. Figure 7 shows the relation between the sparsity of embedding vectors and the stream distributions (n=5K, B=9KB, Wq, AMS). We select the meta-tasks under *Zipf*, *Triangular*, and *Uniform* distributions with different skewness levels (see supplement materials[3] for detailed setup). The results show that the sparsity of the embedding vector is positively proportional to the skewness of a distribution. Therefore, we speculate that the meta-sketch memorizes the pattern information of the distribution being adapted by self-tuning the sparsity of embedding vectors.

Decoding. The decoding module, as the deepest NNs in the meta-sketch, integrates various information to predict the item frequency and achieves generalization ability. To verify this, we adapt the advanced MS (n=5K, B=9KB, Wq) to a special adaptive meta-task. The meta-task was sampled from the real data stream but with a fixed item size (5000) and frequency mean (250). Meanwhile, we do not change the correspondence between items and frequencies. Such meta-task forces the meta-sketch to pay more attention to the fixed patterns and thus limit its generalization.

Thus, we train the advanced MS with (or without) freezing the decoding module parameters based on the above meta-task. Figure 8 (a) shows the performance changes of the three models (advanced MS as baseline) on the evaluation tasks (T_r) of different item sizes. Without the frozen decoding module, the meta-sketch loses generalization ability at extended item sizes other than 5000. On the contrary, the meta-sketch with the frozen decoding module still retains the generalization ability and further utilizes the data stream pattern compared to the advanced MS, achieving the best performance. Similarly, as shown in Figure 8 (b), the meta-sketch without the frozen decoding module also loses a certain generalization ability in terms of frequency mean.

Actually, the above meta-task (termed as *stable case*) can be viewed as a special case of an ordinary adaptive meta-task (termed as *unstable case*), and augmented sketches utilize frequency patterns similar to the stable case. For example, the learned augmented sketch memorizes (relatively) stable correspondence between items and frequencies, for filtering high-frequency items. To understand the meta-sketch's self-optimizing mechanism from the unstable case to the stable case, we analyze the storage of high/low-frequency items between multiple slots and a single slot in the memory. In Figure 9 (a), we show density heat-maps of low-frequency (below the top 20% high frequencies) items, stored by meta-sketches of stable and unstable cases on a 2D slice of the M, where the x-axis is the index of slots. The two heat-maps show that the meta-sketch under the stable case can store the low-frequency items concentratedly in some slots to avoid conflicts with high-frequency items. Interestingly, the meta-sketch does not intentionally do this like augmented sketches. Instead, it is achieved by self-optimization during the training. Furthermore, Figure 9 (b) shows the relation between the sparsity of the embedding vector of items stored in a single slot and the frequency order, where the x-axis represents the frequencies in the ascending order. We speculate that the meta-sketch autonomously adjusts the sparsity of the embedding vector within a single slot in the stable case, so that the high/low-frequency items are automatically separated.

Conclusion

In this paper, we propose a neural data structure: meta-sketch, for estimating item frequencies in data streams. Unlike traditional sketches, the meta-sketch utilizes meta-learning and memory-augmented neural networks. The meta-sketch is pre-trained with *Zipf* distributions and can be fast adapted to specific runtime streams. We study a series of techniques for constructing the meta-sketch. Extensive empirical studies on real datasets are done to evaluate our proposals. In the future, it is interesting to extend our proposal to other sketching tasks that are supported by traditional sketches.

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