# MS&E 317/CS 263: Algorithms for Modern Data Models, Spring 2014

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# 6 Sketches

#### 6.1 Definition

Sketeches are a useful "summary" of a set S. More formally,

**Definition**: A sketch is a couple  $\langle \sigma, \tau \rangle$  where, for any sets  $S_1, S_2$ , the following property is verified:  $\sigma(S_1 \cup S_2) = \tau(\sigma(S_1), \sigma(S_2))$ .

A few exaples where sketches are useful Sketches are very useful for map-reduce jobs. For instance if we want to to the job

```
\overline{\text{MAP}}: \langle a, b \rangle
\text{emit} \langle a, b \rangle
\text{REDUCE:} \langle a, \{b_1, \dots, b_K\} \rangle
\text{emit} \langle a, f(\{b_1, \dots, b_K\}) \rangle
```

Using a skeths allows us to use a combibner and diminish the shuffle size. Now the reduce phase is:

```
REDUCE: \langle a, (\sigma(S_1), \dots, \sigma(S_J)) \rangle
emit \langle a, f(\tau(\sigma(S_1), \dots, \sigma(S_J)) \rangle
```

Sketeches are also useful in a streaming environment. Suppose we need to compute at time t on the whole stream. We would like to compute  $f(\{a_1, \ldots, a_t\})$ . With sketches we can easily do

```
Initialization: \sigma(\{\})
At time t : update \tau(\sigma(S_{t-1}), \sigma(a_t))
```

#### 6.2 Desirable qualities

To be useful, a sketch should have the following properties:

- Computing sigma should be linear
- We should be able to estimate f efficiently and accurately from  $\sigma$

- $\sigma$  should be small
- $\tau$  should be efficient

#### 6.3 A few reminders

### Linearity of the Expectation

If  $X_1, X_2$  are random variables then  $E[X_1 + X_2] = E[X_1] + E[X_2]$ 

# Markov inequality

If X is a positive or null random variable then  $\mathbb{P}(X > cE[X]) < \frac{1}{c}$ 

## Chernoff bounds

If  $S = \sum_{i=1}^{k} X_i$  where  $X_i$  are independent random variables drawn from a Bernouilli distribution, then

$$\mathbb{P}(S < (1 - \delta)\mu) \le e^{\frac{-\delta^2 \mu}{2}}$$

And

$$\mathbb{P}(S > (1+\delta)\mu) \ge \left(\frac{e^{\delta}}{(1+\delta)^{1+\delta}}\right)^{\mu}$$

We can see in the second inequality that as  $\delta \longrightarrow 0$  the right hand side is equivalent to  $e^{-\frac{\delta^2 \mu}{2}}$ 

# 6.4 First example of a Sketch

We would like to find a sketch for the function : f(S) = uniform sample from S.

**Attempt 1**  $\sigma(S) = \text{uniform sample from } S \text{ and } \tau(\sigma(S_1), \sigma(S_2)) \text{ a random choice from } \sigma(S_1), \sigma(S_2)$ That doesn't work if the size of the sets are different.

**Attempt 2** To counter the flaw of the first attempt, we can try to modify  $\tau$  and  $\sigma$  by keeping the size of the sample in memory :

$$\sigma(S) = \langle uniform \ sample \ of \ S, |S| \rangle$$

And 
$$\tau(\langle v_1, s_1 \rangle, \langle v_2, s_2 \rangle)$$
 gives  $\langle v_1, s_1 \rangle$  with  $t = \frac{s_1}{s_1 + s_2}$  and  $\langle v_2, s_2 \rangle$  with  $t = \frac{s_2}{s_1 + s_2}$ 

This method doesn't work if the sets  $\sigma(S_1)$ ,  $\sigma(S_2)$  aren't disjoint. To give a proper solution, we need to define the notion of a Consistent random Hash function.

#### Consistent random Hash function

A Consistent random Hash function h(x) verifies

- h(x) follows a uniform law on [0,1]
- h(x) and h(y) are independent for any  $x \neq y$
- h(x) returns the same calue each time for a given x

For instance, in any modern programmation language, one could write:

def h(x) srand (x)return rand()

We are now ready to give the solution

#### Solution

Let h be a Consistent random Hash function. We define

$$\sigma(S) = argmin_{x \in S}h(x)$$

and

$$\tau(\sigma_1, \sigma_2) = argmin_{x \in \sigma_1, \sigma_2} h(x)$$

This two functions define a sketch and give an accurate response to our problem.

### 6.5 Second example of a sketch

In this case we consider a streaming example  $a_1, \ldots, a_t$  and try to evaluate the frequency of each item in the stream  $f_t(a) = |\{i \le t | a_i = a\}|$  and we also define the  $k^{th}$  frequency moment

$$F_k(t) = \sum_{a \in V} (f_t(a))^k \ k > 0$$

and  $F_0(t)$  as the number of distinct values in the stream seen at time t.