# 592 Project Report

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## Project Report 592 Project in Data Science

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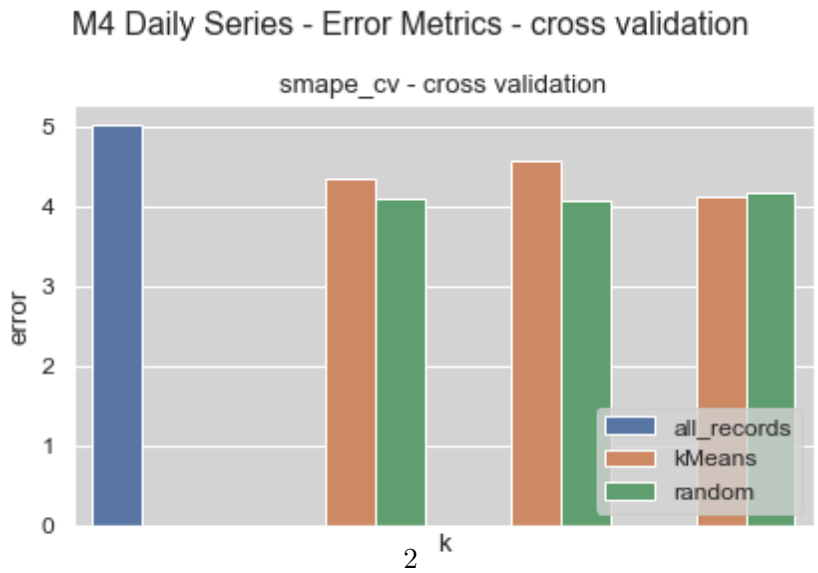
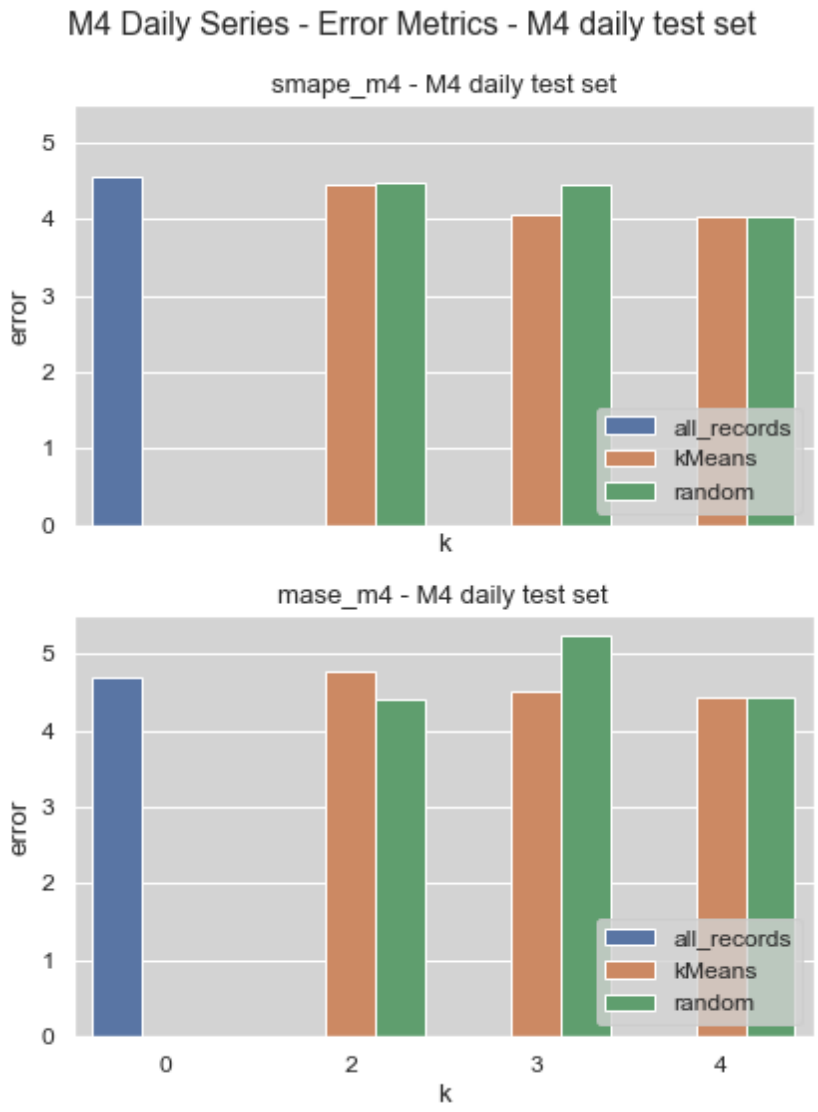


**Results on M4 test set**



**results not better than random**

**Uncertainty in the clustering**

**How to measure similarity**

**Ts representation**

**Distance metrics**

**Clustering algorithms**

**Limitations**

**Conclusions**

#### this the old template

# Flajolet-Martin Implemenation

`https://552dlimages.s3-eu-west-1.amazonaws.com/unic_logo.png`

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### Counting cardinalities of Wikipedia entries

University of Nicosia
COMP 552DL - Data Privacy and Ethics
Prof. Dr. Thomas Liebig

# Motivation

- counting cardinalities with limited resources (Big Data)
- flow monitoring from stationary sensors

### Wikipedia Entry Cardinalities

- Wikipedia large variety of cardinalities across its entries
- readily available API for data ingestion

# Flajolet-Martin Algorithm

## Basic Estimation Approach

### Hash Function

word is denoted as:

$$x = (x_0, x_1, \ldots, x_p)$$

Elements of x are hashed via:

$$hash(x) = (M + N \sum_{j=0}^{p} ord(x_j) 128^j) \, mod \, 2^L$$

### Resulting Integer

is considered in its bit form:

$$y = \sum_{k \geq 0} bit(y, k) \, 2^k$$

where p(y) represents the postion of the least-significant set bit.

### Bitmap

$$p(y)$$

for each word in stream is stored in a

$$bitmap[0 \ldots L-1]$$

- Length of Bitmap

$$L > log_2(n/nmap) + 4$$

### Expected Behavior

If n is the number of distinct elements in M then:

- bitmap[0] is accessed approximately n/2 times
- bitmap[1] is accessed n/4 times
- ...

**In consequence**

$$i \gg \log_2 n$$

is expected to be zero

$$i \ll \log_2 n$$

is expected to be one

$$i \approx log_2\, n$$

has a fringe of zeros and ones

**Bias Factor**

Flajolet and Martin identified a bias factor:

$$\varphi = 0.77351\cdots$$

**Standard Deviation**

Flajolet and Martin prove that under reasonable probablistic assumptions:

$$\sigma(R) \approx 1.12$$

Therefore, result is typically 1 binary order of magnitude off (correction via nmap)

**NMAP**

Set of Hashing functions for each word

$$A = \frac{R_1 + R_2 + \cdots + R_m}{m}$$

## PCSA

Probabilistic Counting with Stochastic Averages

**Modification to basic approach**

- use hashing function in order to distribute each word into one of m lots via:

  $$\alpha = h(x)\, mod\, m$$

- update corresponding bitmap vector of alpha from h(x)

  $$h(x)\, div\, m$$

  (floored)

### Expectation

- distribution of records falls evenly into lots so that

$$(1/\varphi)\, 2^A$$

  is a reasonable approximation

## Implementation

### Hash Function

```
def hash_val(self, word: str, v: int, w: int) -> int:
        l = list(word)
        term1: int = 0
        for i in range(len(l)):
            term1 += ord(l[i])*128**i
        return int((v*term1 + w) % 2**self.L)
```

### Updating the bitmap

```
def update_bitmap(self, word: str) -> None:
         # calculate hash value
         for i in range(self.nmap):
             # calculate hash with current set of values
             hash_val = self.hash_val(word=word,
                                      v=self.vs[i],
                                      w=self.ws[i])
             # find rightmost set bit in hash value
             r = self.rightmost_set_bit(hash_val)
             if r == None:  # cases need to be ignored as element value is 0
                 continue
             assert type(r) == int, 'r must be int'
             if self.bitmaps[i, r] == 0:
                 self.bitmaps[i, r] = 1
```

### Rightmost Set Bit

```
def rightmost_set_bit(self, v: int) -> int:
         # using bit operations to identify position
         # of least significant set bit
         if v == 0:
             return None
         return int(math.log2(v & (~v + 1)))
```

### Basic Estimation Approach

```
def fm(self) -> int:
        # allowing for hashing of entire stream
        vbitmap_update = np.vectorize(self.update_bitmap)
        # contains hashed values for each element in stream
        vbitmap_update(self.data_stream)

        if self.optimization == 'reduce':
            # reduce bitmap
            red_bitmap = self.reduce_bitmaps(self.bitmaps)
            R = self.leftmost_zero(red_bitmap)
            return self.C*2**R
        elif self.optimization == 'mean_r':
            R = np.zeros((self.nmap,))
            for i in range(self.nmap):
                R[i] = self.leftmost_zero(self.bitmaps[i, :])
            mean_R = np.mean(R)
            return self.C*2**mean_R
```

### PCSA Approach

```
def pcsa_bitmap(self, word: str) -> None:
    hashedx = self.hash_val(word=word,
                            v=self.m,
                            w=self.n)
    alpha = hashedx % self.nmap
    beta = math.floor(hashedx/self.nmap)
    assert isinstance(beta, int), "index is integer"
    idx = self.rightmost_set_bit(beta)
    self.bitmaps[alpha, idx] = 1

def fm_pcsa(self) -> int:
    # allowing for hashing of entire stream
    vbitmap_update = np.vectorize(self.pcsa_bitmap)
    # contains hashed values for each element in stream
    vbitmap_update(self.data_stream)
    S = 0
    for i in range(self.nmap):
        R = 0
        while (self.bitmaps[i, R] == 1) and (R < self.L):
            R += 1
        S += R
    return math.floor(self.nmap/self.phi*2**(S/self.nmap))
```

## Results

### Search Terms

| Search Term | Size | True Unique Values |
|---|---|---|
| List of fatal dog attacks in the United States (2010s) | small | 54 |
| Weisswurst | small | 265 |
| university of nicosia | small | 1035 |
| data privacy | small | 1049 |
| Timeline of the Israeli–Palestinian conflict 2015 | medium | 1406 |
| covid | medium | 1657 |
| List of Crusades to Europe and the Holy Land | medium | 2464 |
| michael jordan | medium | 2529 |
| List of University of Pennsylvania people | large | 2928 |
| Donald Trump | large | 4633 |
| 2020 Nagorno-Karabakh war | large | 4643 |
| List of association football | large | 5883 |

### Low Count Entries

`https://552dlimages.s3-eu-west-1.amazonaws.com/distribution_small.png`

### Medium Count Entries

`https://552dlimages.s3-eu-west-1.amazonaws.com/distribution_med.png`

### Large Count Entries

`https://552dlimages.s3-eu-west-1.amazonaws.com/distribution_large.png`

## Discussion

- basic estimation is consistent and provides better accuracy compared to PCSA implementation
- PCSA has large distribution
- methods perform worst with low count streams
- PCSA becomes more performant with increase of unique values
- PCSA has significant compute performance advantage

### Next Steps

- improve hashing function for PCSA approach
- review LogLog, SuperLogLog, HyperLogLog and review their increase in accuracy (trade-offs performance / accuracy)