Mining temporal data – Frequent sequences

Algorithmic Data Analysis - Coding Assignment 2

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Resources: No resources

Collaborations: No collaborations

The Generalized Sequential Pattern Mining (GSP) algorithm is an apriori-like algorithm for solving sequential pattern mining, here I try to implement it in Python and use it for mining frequent patterns from discrete sequences. The algorithm is then applied to the CRSW dataset, which contains two months worth of weather data in Kuopio (January–February 2019).

GSP algorithm implementation idea

The implemented algorithm takes a dataset (list of itemsets) and a minimum support threshold. It first identifies frequent items (items with support greater than or equal to the minimum support threshold). Then, starting from k = 1, it iteratively generates candidate sequences of length k + 1 by joining pairs of sequences from the frequent patterns of length k. The support of these candidates is calculated and only those with support greater than or equal to the minimum support threshold are retained. This process continues until no more frequent patterns can be found. The output of the code is a dictionary where the keys are the frequent patterns and the values are their corresponding support counts.

Application to the CRSW dataset

The weather time series analysis using the Generalized Sequential Pattern (GSP) mining algorithm has revealed interesting patterns in the occurrences of clouds (C), precipitation (R), sunshine (S), and wind (W).

Setting different minimum support threshold

If we set the minimum support threshold to 30, we get three frequent patterns:

- 'CRW', with a support of 225. This is cloudy, rainy and windy weather.
- 'CR', with a support of 99. This is cloudy and rainy weather.
- 'CW', with a support of 237. This is cloudy and windy weather.

Setting different values for max gap and max span

If we change the values for max gap and max span we can obtain these different results:

Min supp thresh	Max span	Max gap	Frequent patterns
10	5	10	[('CRW', 225), ('CR', 99), ('CW', 237)]
1	1	1	[('CRW', 75), ('CR', 99), ('CW', 237)]
200	20	20	[('CW', 237)]
100	10	10	[('CRW', 225), ('CW', 237)]

Table 1: Frequent patterns using different parameters

A. Code

```
1 import copy
2 ## GSP
{\scriptscriptstyle 3} # implementation of the generalized sequential pattern mining (GSP) algorithm for
      mining frequent patterns from discrete sequences
5 # def get_sequences_from_file(file_path):
6 #
         sequences = []
7
  #
        with open(file_path, 'r') as file:
8
  #
             for line in file:
9
  #
                 timestamp, sequence = line.strip().split()[0], line.strip().split()[1:]
10
  #
                 sequences.append(sequence)
11
  #
        return sequences
12
  def get_sequences_from_file(file_path):
13
      sequences = []
14
      with open(file_path, 'r') as file:
           for line in file:
16
               timestamp, sequence = line.strip().split()[0], line.strip().split()[1:]
17
               split_sequence = [list(itemset) for itemset in sequence]
18
               sequences.append(split_sequence)
19
20
      return sequences
21
22
23
24
  def join_sequences(frequent_items, maxspan, maxgap):
25
      # candidate (k + 1)-sequences are generated by combining pairs of frequent k-
      sequences
      candidates = []
26
27
      # Fix a canonical order on the sequences and ensure that each candidate (k + 1)-
28
      subsequence is generated by only one pair of k-sequences ??
      for i in range(len(frequent_items)):
31
           Sa = list(frequent_items[i])
32
33
           for j in range(len(frequent_items)):
34
35
               Sb = list(frequent_items[j])
36
37
               Sc = []
38
39
               if check_candidate_gen(Sa,Sb) != 0:
40
                   # If the first itemset of Sa is a singleton, Sc is generated by
41
      prepending it to Sb
                   if len(list(Sa)[0]) == 1: # here I'm checking if the list
42
                        Sa = "".join(Sa)
43
                        Sb = "".join(Sb)
44
                        Sc.insert(0, Sa)
45
                        Sc.append(Sb)
46
47
                        Sc = "".join(Sc)
48
                        candidates.append(Sc)
```

```
# If the first itemset of Sa is not a singleton, Sc is generated by
50
       replacing the first itemset of Sb with it
                    elif len(list(Sa)[0])>1:
51
                        Sa = "".join(Sa)
52
                        Sb = "".join(Sb)
                        Sc.insert(0,Sa)
                        Sc.append(Sb[1:])
                        Sc = "".join(Sc)
56
                        candidates.append(Sc)
57
58
                    # If the last itemset of Sb is a singleton, Sc is generated by
59
       appending it to Sa
                    elif len(list(Sb)[-1]) == 1:
60
                        Sa = "".join(Sa)
61
                        Sb = "".join(Sb)
62
                        Sc.append(Sa)
                        Sc.append(Sb[-1])
64
                        Sc = "".join(Sc)
65
66
                        candidates.append(Sc)
67
                    # If the last itemset of Sb is not a singleton, Sc is generated by
68
       replacing the last itemset of Sa with it
                    elif len(list(Sb)[-1])>1:
                        Sa = "".join(Sa)
70
                        Sb = "".join(Sb)
71
                        Sc.append(Sa[0:(len(Sa)-2)])
72
                        Sc.append(Sb[-1])
73
                        Sc = "".join(Sc)
74
75
                        candidates.append(Sc)
76
       return candidates
77
78
   def check_candidate_gen(Sa, Sb):
79
       # removing an item from the first itemset of Sa and removing an item from the
80
       # last itemset of Sb should result in the same sequence So
81
82
       Sa1 = [list(item) for item in Sa]
       Sb2 = [list(item) for item in Sb]
85
86
       Sa_red = copy.deepcopy(Sa1)
       Sb_red = copy.deepcopy(Sb2)
87
88
       # first itemset of Sa: Sa_red[0]
89
       # last itemset of Sb: Sb_red[-1]
90
91
       k = 0
92
93
       for i in range(len(Sa_red[0])):
           # remove an item from the first itemset of Sa
95
96
           if i == len(Sa_red[0]):
97
                break
98
           Sa_red[0].pop(i)
           Sa_red = [item for item in Sa_red if item != []]
99
100
           for j in range(len(Sb_red[-1])):
           # remove an item from the last itemset of Sb
102
103
                if j == len(Sb_red[-1]):
                    break
                Sb_red[-1].pop(j)
                Sb_red = [item for item in Sb_red if item != []]
106
                k += (Sa\_red == Sb\_red)
108
109
                Sb_red = copy.deepcopy(Sa1)
110
           Sa_red = copy.deepcopy(Sb2)
111
112
```

```
#print(k)
113
       return k
114
115
116 def is_subsequence(candidate, sequence, max_span, max_gap):
117
       # CONSTRAINTS
118
       # 1. maximum span limit the time difference between the first and last itemsets
119
       of a subsequence
       # 2. maximum gap limit the number of gaps between successive itemsets of a
120
       subsequence
       # Initialize indices for candidate and sequence
       i, j = 0, 0
123
       span_start = None
124
       # Iterate through both lists
       while i < len(candidate) and j < len(sequence[0]):
127
           \mbox{\tt\#} If the elements match, move to the next element in both lists
128
           if candidate[i] == sequence[0][j] and abs(i-j) < max_gap:</pre>
129
                if span_start is None:
130
                    span\_start = j # Start of the span
131
           # Move to the next element in the larger list
134
           j += 1
135
       # If all elements of the candidate list are found in the sequence in the same
136
       order, check constraints
       if i == len(candidate):
137
           span_end = j - 1 # End of the span
138
           span_length = span_end - span_start
139
140
           # Check constraints
141
           if span_length <= max_span:</pre>
142
                return True
143
144
       return False
146
   def count_support(dataset, candidates, maxspan, maxgap):
147
148
149
       support = {}
       # the support of subsequence S in sequence D is the number of occurrences of S in
151
       for candidate in candidates:
152
           candidate = list(candidate)
           for itemset in dataset:
154
                if is_subsequence(candidate, itemset, maxspan, maxgap):
                    itemset = "".join(itemset[0])
156
                    if itemset in support:
157
158
                         support[itemset] += 1
159
                    else:
                         support[itemset] = 1
160
161
       return support
163
  def gsp(dataset, minsup, maxspan, maxgap):
164
165
       item_counts = {}
166
167
       # Fk: all frequent items
168
169
       # count support of items.... or itemsets?
170
       for sequence in dataset:
           for itemset in sequence:
172
                for i in itemset:
173
                    if i in item_counts:
174
```

```
item_counts[i] += 1
                    else:
                        item_counts[i] = 1
177
178
       # itemsets:
179
       # for sequence in dataset:
180
             for itemset in sequence:
181
                 key = ''.join(itemset)
182
       #
                 if key in item_counts:
183
                      item_counts[key] += 1
184
                 else:
185
                      item_counts[key] = 1
186
187
188
       frequent_items = {item: count for item, count in item_counts.items() if count >=
189
      minsup}
       result = {}
191
192
       # while Fk != 0
193
       while len(frequent_items)!=0:
194
195
           \# generate C_k+1 by joining pairs of sequences from F_k
196
           candidates = join_sequences(list(frequent_items.keys()), maxspan, maxgap)
197
           candidate_support = count_support(dataset, candidates, maxspan, maxgap)
198
           # S in C_k+1
           frequent_items = {pattern: support for pattern, support in candidate_support.
      items() if support >= minsup} # add to result if the support is > minsup
           result.update(frequent_items) # F_k+1
202
203
           k += 1
204
205
       return result # dict object made of 'pattern' and 'support'
206
207
208 ## Apply the algorithm on the CRSW dataset:
209 # '2019-01-03_itemsets-CRSW.txt' Two months worth of weather in Kuopio (
       January February 2019), obtained from https://en.ilmatieteenlaitos.fi/download-
      observations#!/
210 # Each line represents weather events during one hour as an itemset. The first column
        contains the contextual attribute, i.e. indication of time in Year-Month-
      Day_Hour format.
211 # The second column contains the itemset. C, R S and W stand respectively for clouds,
       precipitation, sunshine and wind.
213 file_path = "2019-01-03_itemsets-CRSW.txt"
214 \text{ minsup} = 100
215 \text{ maxspan} = 10
216 \text{ maxgap} = 10
217 dataset = get_sequences_from_file(file_path)
218 result = gsp(dataset, minsup, maxspan, maxgap)
219
220 # Print the frequent patterns
221 print(f"Minimum support threshold = {minsup}")
222 print(f"Maximum span = {maxspan}")
223 print(f"Maximum gap = {maxgap}")
224 print("Frequent patterns:")
225 print(list(result.items()))
227 # Try diff erent values for the mininum support threshold, diff erent constraints
      such as max gap and max span,
228 # and considering the data either as one long sequence or with each day as a separate
       short sequence. You might
229 # also try replacing repeated occurrences of the same itemset by a single copy, i.e.
      represent constant weather
230 # during successive hours with only one itemset.
```

Report on the type and number of patt erns obtained under diff erent conditions.