Big Data Lab

May 2, 2016

Spark’s MLlib

- MLlib is Spark’s machine learning library
- Goal is to make practical machine learning scalable and easy
- Includes common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, lower-level optimization primitives and higher-level pipeline APIs

FP-Growth

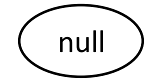
- “FP”=“frequent pattern”
- Like apriori-like algorithms, the first step of FP-growth is to calculate item frequencies and identify frequent items
- Unlike apriori-like algorithms, the second step of FP-growth uses a suffix tree (FP-tree) structure to encode transactions without generating candidate sets explicitly
- Based on the paper Han, Pei, and Yin, “Mining frequent patterns without candidate generation”, SIGMOD, 2000.

FP-Growth

- After the second step, the frequent itemsets can be extracted from the FP-tree.
- spark.mllib implements a parallel version of FP-growth called PFP, as described in Li et al., PFP: Parallel FP-growth for query recommendation
- PFP distributes the work of growing FP-trees based on the suffices of transactions, and hence more scalable than a single-machine implementation
- Spark's FP-Growth implementation takes the following parameters:
  - minSupport: the minimum support for an itemset to be identified as frequent. For example, if an item appears 3 out of 5 transactions, it has a support of 3/5=0.6.
  - numPartitions: the number of partitions used to distribute the work

Han, Pei, and Yin, “Mining frequent patterns without candidate generation”, SIGMOD, 2000

Example



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400	b, c, k, s, p	c, b, p
500	a, f, c, e, l, p, m, n	f, c, a, m, p

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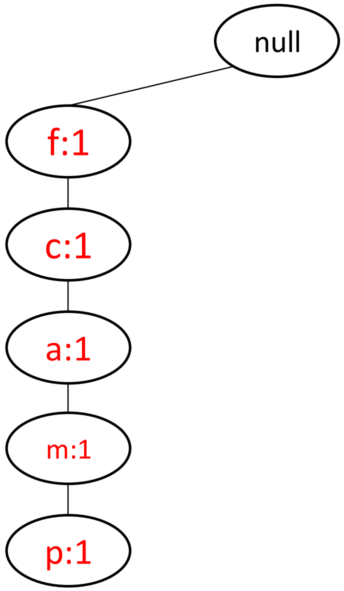

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- Second scan of the DB:
- Scan of first transaction leads to first branch of the tree: <(f:1), (c:1), (a:1), (m:1), (p:1)>

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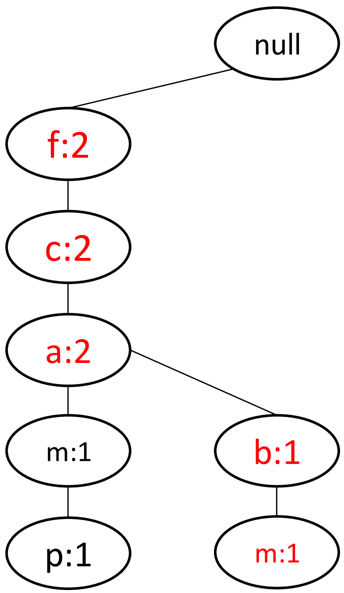

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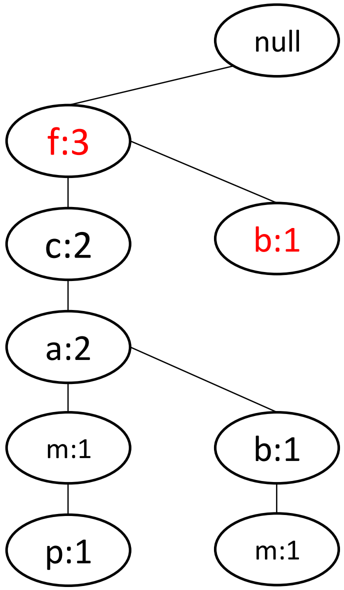

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- Third transaction: f’s count is incremented by 1, (b:1) is created as a child of (f:3)

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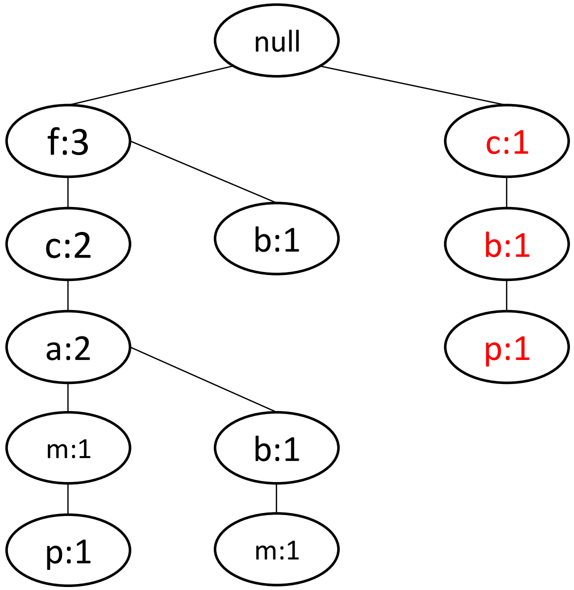

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- Fourth transaction: Since no prefix in common, create the second branch of the tree <(c:1), (b:1), (p:1)>

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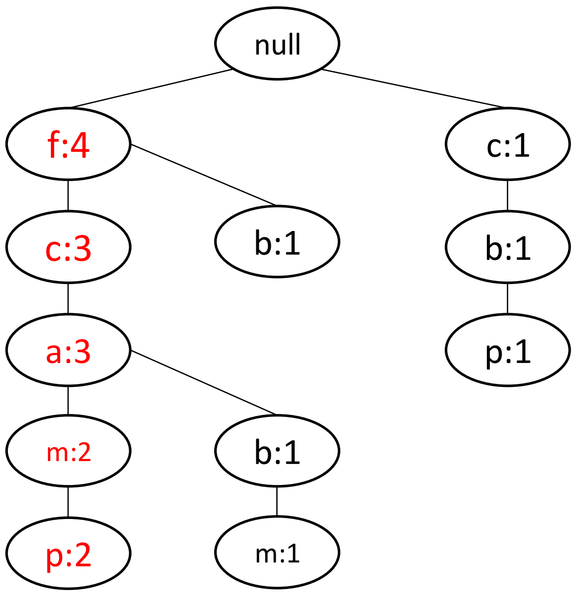

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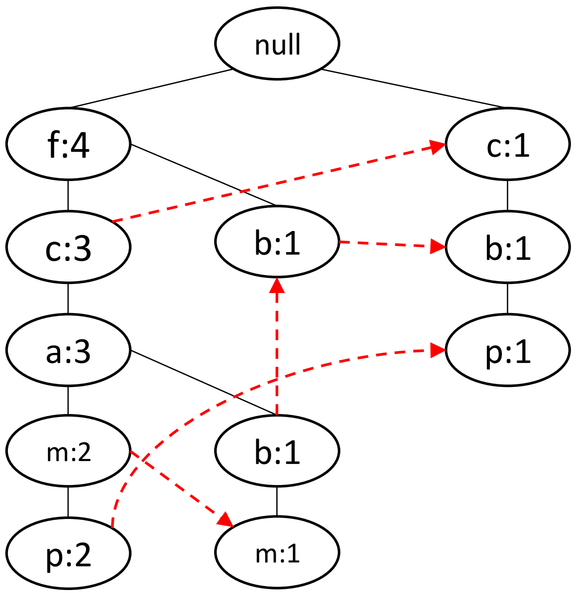

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- Nodes with the same item name are linked via “node-links”

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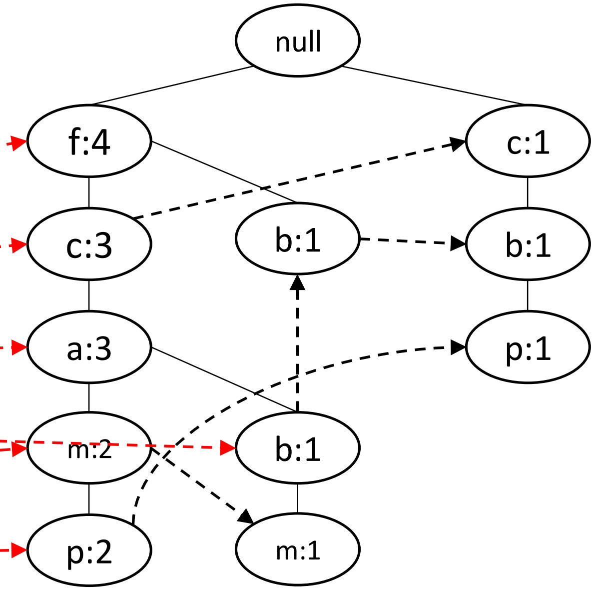
Example

Header Table

Item	Head of node-links
f	
c	
a	
b	
m	
p	



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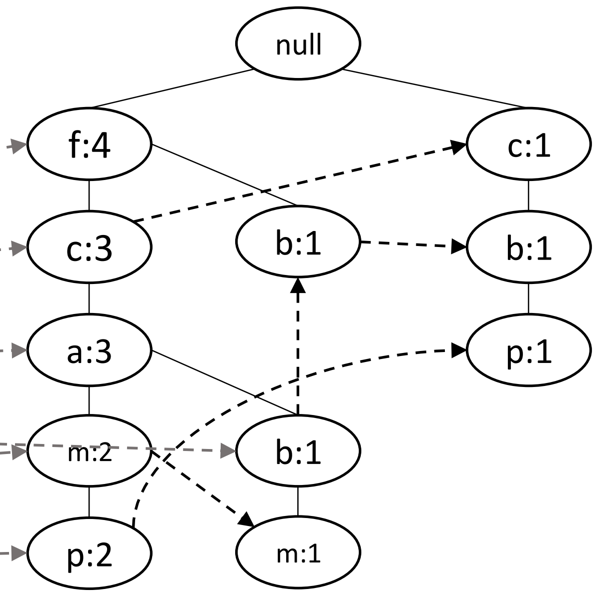

- Mining frequent patterns
- Collect all patterns that a node x participates in by starting from x's head (in the header table) and following x's node-links

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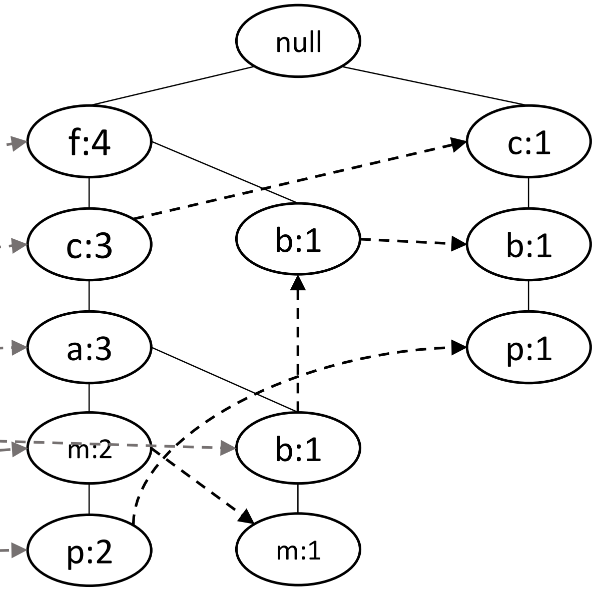

- Mining frequent patterns
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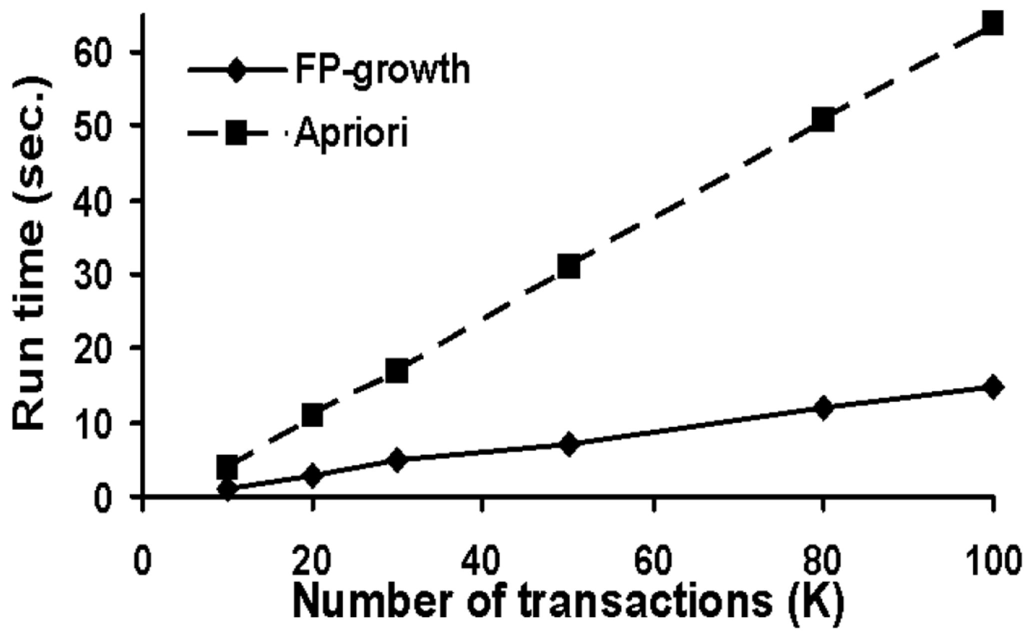
- Example: item p
- Node p derives a frequent pattern (p:3) and two paths in the FP tree: <f:4, c:3, a:3, m:2, p:2> and <c:1, b:1, p:1>
  - The first path indicates that the string (f,c,a,m,p) appears twice in the DB
  - Second path indicates that (c,b,p) appears once in the DB
- Since both paths contain (c,p), this is a frequent pattern, (cp:3)

Benefits

- Apriori-like algorithms can generate an exponential number of candidates in the worst case, but size of an FP-tree is bounded by the size of its database
- Can lead to faster runtime



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In PySpark

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from pyspark.mllib.fpm import FPGrowth

data = sc.textFile("data/mllib/sample_fpgrowth.txt")

transactions = data.map(lambda line: line.strip().split(' '))

model = FPGrowth.train(transactions, minSupport=0.2, numPartitions=10)



result = model.freqItemsets().collect()

for fi in result:
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takes an RDD of transactions, where each transaction is an List of items of a generic type

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Could access item list by fi.items, frequency by fi.freq

Resources

- https://spark.apache.org/docs/latest/mllib-frequent-pattern-mining.html

- https://spark.apache.org/docs/latest/api/python/pyspark.mllib.html#pyspark.mllib.fpm.FPGrowth