User Manual of Felix 0.2

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1 Overview

Felix is a relational optimizer for statistical inference.

Recent years have seen a surge of sophisticated statistical frameworks with the relational data model (via SQL/logic-like languages). Examples include MLNs and PRMs. While this movement has demonstrated significant quality advantage in numerous applications on small datasets, efficiency and scalability have been a critical challenge to their deployment in Enterprise settings. Felix addresses such performance challenges with an operator-based approach, where each operator performs a statistical algorithm with relational input/output. The key observations underlying Felix are

1. **Task Decomposition**: Conventional approaches to statistical-relational inference are monolithic in that, not only do they express complex tasks in a "unified" language, they also attempt to solve the tasks by running a generic algorithm (e.g., random walk, greedy, or sampling) over the entire program. This often results in poor quality and/or miserable scalability. On the other hand, a complex task often consists of subtasks that have specialized algorithms with high quality and high efficiency. For example, many text analytics tasks can be decomposed into a handful of primitives such as classification, clustering, and ranking. And so a natural question is: Why not combine the ease and flexibility of the "unified" language with the high quality and efficiency of specialized (statistical) algorithms? That is what Felix does.

2. **Data Partitioning**: Parallelism is king of scalability. The king is happy when the data can be partitioned in embarrassingly obvious ways. However, the king is often puzzled in front of complex statistical tasks; the point of such tasks, after all, is to embrace rich correlations. Felix is set to find ways to identify parallelization opportunities in complex statistical tasks, automatically.

In this prototype implementation of Felix , we take Markov logic [3, 1] as the "unified" language to express sophisticated statistical tasks. Markov logic adds weights to first-order logic rules, and has rigorous semantics based on the exponential models. It has been successfully applied to a wide range of applications including information extraction, entity resolution, text mining, and natural language processing. Nevertheless, state-of-the-art implementations of Markov logic (e.g., Alchemy [1] and our own Tuffy [2]) are unaware of the above optimization opportunities that motivated Felix , and so suffer from suboptimal quality and scalability.

Felix takes as input a Markov logic program (with evidence data), and outputs the same kinds of predictions as what Alchemy and Tuffy would output given the same input (if they can run, that is). Internally, Felix performs the following steps

1. **Compilation**: identifies specialized subtasks in the program and assign them to a predefined set of statistical operators, including logistic regression (LR), conditional random field (CRF), correlation clustering (CC), and Tuffy – the generic MLN inference engine.

2. **Optimization**: applies cost-based data materialization strategies to ensure the efficiency of data movement between operators.

3. **Execution**: partitions the data with linear programming, so that one operator can process the data in parallel.

Some technical highlights in Felix 0.2:

[1] http://alchemy.cs.washington.edu/
[2] http://research.cs.wisc.edu/hazy/tuffy

- **Three Specialized Operators**: Felix will discover Logistic Regression (for classification), Conditional Random Field (for sequential labeling), and Correlation Clustering (for clustering or coreference) subtasks in the input program and solve them using specialized algorithms (Viterbi, etc.).
- **Data Movement Optimization**: Explicitly materializing intermediate data could blow up easily. Felix avoids the explosion of data movement between operators with a novel cost-based materialization strategy that utilizes the RDBMS's optimizer.
- **Multi-core Parallelism**: Felix will partition the input data and run sub-operators on different portions concurrently to exploit multi-core CPUs.

For further technical details about Felix , please read our technical report [2] or visit our website at http://research.cs.wisc.edu/hazy/felix.

This manual provides essential information about how to install, set up and execute Felix . Hereinafter, we assume the readers are familiar with Tuffy [3]. The current version of Felix only implements inference. Users interested in weight learning should refer to Tuffy instead.

2 Installation

2.1 Installing Prerequisites

Felix has almost the same setup procedure as Tuffy . Please visit Tuffy 's website (http://research.cs.wisc.edu/hazy/tuffy/doc) for details.

2.2 Configuring Felix

Download the latest version of Felix from . After unpacking, you should see a configuration file named "felix.conf". This file contains necessary information Felix will use for execution. Please refer to Tuffy 's website (http://research.cs.wisc.edu/hazy/tuffy/doc) for explanations of this configuration file.

3 Usage Example

In this section, we use an example to demonstrate how to run Felix .

Input In the standard case, Felix 's input is exactly the same as Tuffy . (Again, see Tuffy 's documentation for details.) We assume the following three files are provided:

- **prog.mln**: an MLN program file.
- **evidence.db**: a file containing evidence tuples.
- **query.db**: a file specifying the queries.

Figures 1, 2, 3 show the content of these files. See Section 5 for other input options.

You can run Felix with the following command:

[3] http://research.cs.wisc.edu/hazy/tuffy

```
java -jar felix.jar -i prog.mln -e evidence.db -queryFile query.db -r out.db
```

Felix will decompose the input MLN and assign the rules to the following three operators:

- a Correlation Clustering Operator on `tcoref`;
- a Logistics Regression Operator on `label`
- a Tuffy Operator on `dwinner` and `dloser`.

One possible output of this program will be `dwinner("GreenBay", "Dec 10, 2006")`. Felix will generate four output files: "out_dloser", "out_dwinner", "out_label" and "out_tcoref", one for each open predicate. Figure 4 shows a screencast of Felix running this program.????

4 Compilation

4.1 Operators

Felix implements a best-effort compiler to detect subtasks in the given MLN programs. This section will show some syntactical patterns Felix uses to discover specialized subtasks. Users who want exactly these operators can follow these patterns.

Logistic Regression Felix will discover a predicate that can be solved as logistic regression by finding key constraints in predicate declaration:

```
label(seqid, wordid, label!)
```

Felix will also tries to parse hard constraint specifying key constraints like:

```
label(s,w,l), [l != l1] => !label(s,w,l1).
```

If this predicate with key constraint only appears in non-recursive rules, Felix will consider mapping it to a logistic regression operator.

Conditional Random Field Felix will assign a predicate to a conditional random field operator if a predicate has a key constraint (same syntax as Logistic Regression) and appears in non-recursive rules or rules with linear chain recursion of this form:

```
wgt: weight2(l1, l2, wgt), label2(sid, wid1, l1), [wid2 = wid1 + 1] => label2(sid, wid2, l2)
```

```
*word(seqid, wordid, word)
*feature(wordid, feature)
*weight(label, feature, double_)
*seqTime(seqid, date)
*tcrt(word, word)

dwinner(word, date)
dloser(word, date)
label(seqid, wordid, label!)
tcoref(wordid, wordid)
*tcoref_map(wordid, wordid)

tcoref(t1, t1).
tcoref(t1, t2) => tcoref(t2, t1).
tcoref(t1, t2), tcoref(t2, t3) => tcoref(t1, t3).

20 word(seqid1, wordid1, word1), word(seqid2, wordid2, word2),
   tcrt(word1, w), tcrt(word2, w)
   => tcoref(wordid1, wordid2)

wgt: word(seq, id, word), feature(id, feature),
     weight(label, feature, wgt)
     => label(seq, id, label)

5 label(seq, word, "WIN"), tcoref_map(word, word1),
  word(seq1, word1, text1), seqTime(seq, date)
  => dwinner(text1, date)

5 label(seq, word, "LOS"), tcoref_map(word, word1),
  word(seq1, word1, text1), seqTime(seq, date)
  => dloser(text1, date)

5 dwinner(t1, date) => !dloser(t1, date)
```

Figure 1: Sample Input to Felix (prog.mln)

```
seqTime(48, "Dec 12, 2006")
word(48, 1310, "GreenBay")
feature(1310, "U00:GreenBay")
weight("LOS", "U00:GreenBay", 0.0698738377461130)
weight("NON", "U00:GreenBay", 0.4092761660611854)
weight("WIN", "U00:GreenBay", -0.4791500038073283)
tcrt("GreenBay", "GreenBayPackers")
...
```

Figure 2: Sample Input to Felix (evidence.db)

```
dwinner(teamCluster, date)
dloser(teamCluster, date)
```

Figure 3: Sample Input to Felix (query.db)

Correlation Clustering Felix will assign a predicate to a correlation clustering operator if a predicate has hard-constraints associating with it which specify the three properties of equivalent relations:

```
ocoref(a,a). // reflexive
ocoref(a,b), ocoref(b,c) => ocoref(a,c). //transitive
ocoref(a,b) => ocoref(b,a). //symmetric
```

MLN Felix will assign the remaining predicates to the Tuffy operator.

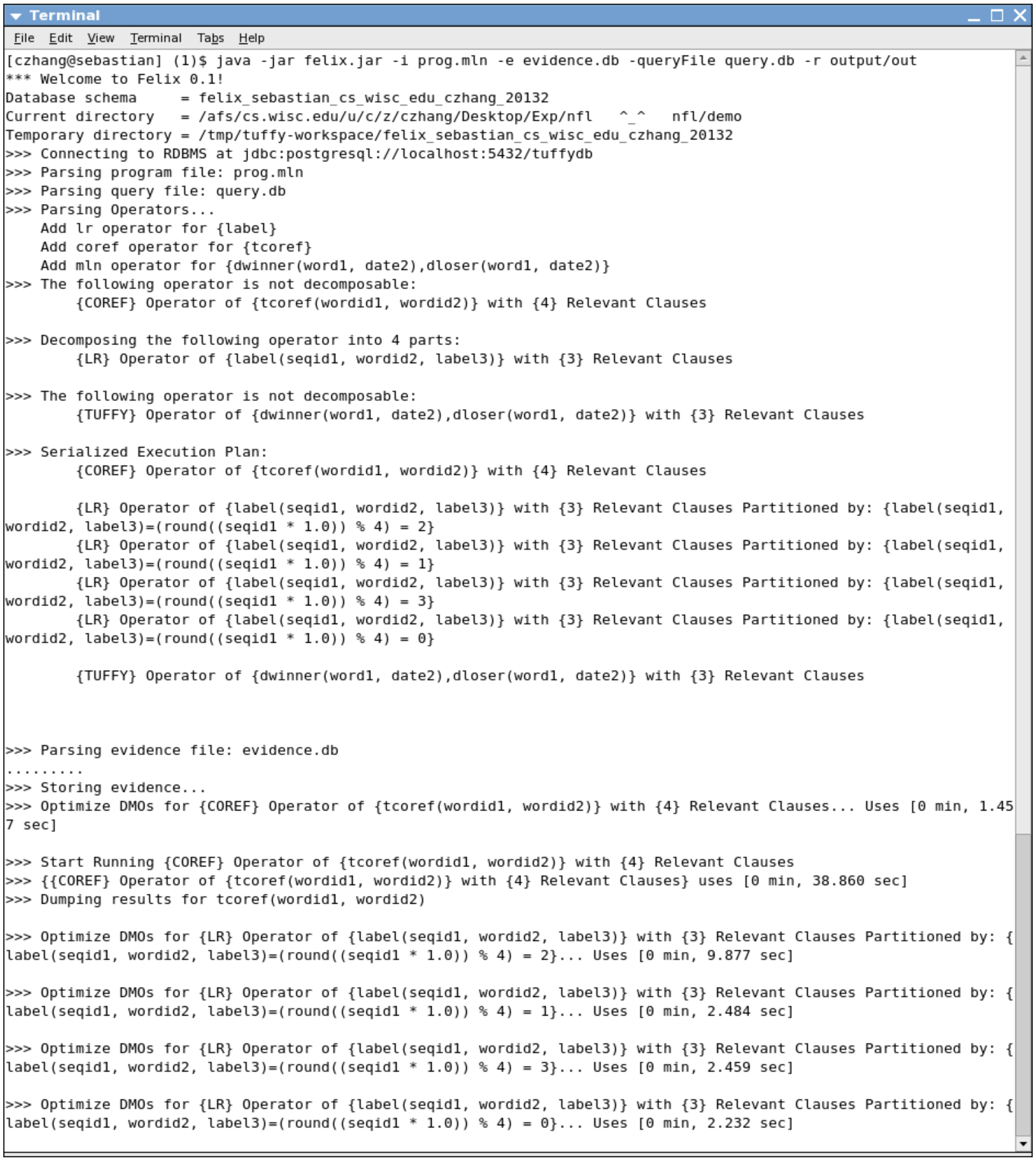
4.2 Special Predicates

Besides standard MLN syntax used by Tuffy , Felix also supports some special syntax. The motivation of these special syntax are to ease the development of MLN programs.

If the program contains a predicate of the form `P(.,.)` that is processed by the CC operator, and in addition there is a predicate of the form `P_map(.,.)`, then the second predicate will also be filled by the CC operator. The content is a linear representation of the clustering result:

$$P\_map(x,y) <=> y \text{ is a representative element of the cluster } x \text{ belongs to.} \tag{1}$$

When dumping the result of `P(.,.)`, Felix actually dumps `P_map(.,.)`'s result because the former can be quadratic in the size of domain. An example of using `P_map(.,.)` can be found in Figure 1.



```
[czhang@sebastian] (1)$ java -jar felix.jar -i prog.mln -e evidence.db -queryFile query.db -r output/out
*** Welcome to Felix 0.1!
Database schema     = felix_sebastian_cs_wisc_edu_czhang_20132
Current directory   = /afs/cs.wisc.edu/u/c/z/czhang/Desktop/Exp/nfl   ^_^   nfl/demo
Temporary directory = /tmp/tuffy-workspace/felix_sebastian_cs_wisc_edu_czhang_20132
>>> Connecting to RDBMS at jdbc:postgresql://localhost:5432/tuffydb
>>> Parsing program file: prog.mln
>>> Parsing query file: query.db
>>> Parsing Operators...
    Add lr operator for {label}
    Add coref operator for {tcoref}
    Add mln operator for {dwinner(word1, date2),dloser(word1, date2)}
>>> The following operator is not decomposable:
        {COREF} Operator of {tcoref(wordid1, wordid2)} with {4} Relevant Clauses

>>> Decomposing the following operator into 4 parts:
        {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses

>>> The following operator is not decomposable:
        {TUFFY} Operator of {dwinner(word1, date2),dloser(word1, date2)} with {3} Relevant Clauses

>>> Serialized Execution Plan:
        {COREF} Operator of {tcoref(wordid1, wordid2)} with {4} Relevant Clauses

        {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {label(seqid1,
wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 2}
        {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {label(seqid1,
wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 1}
        {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {label(seqid1,
wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 3}
        {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {label(seqid1,
wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 0}

        {TUFFY} Operator of {dwinner(word1, date2),dloser(word1, date2)} with {3} Relevant Clauses



>>> Parsing evidence file: evidence.db
.........
>>> Storing evidence...
>>> Optimize DMOs for {COREF} Operator of {tcoref(wordid1, wordid2)} with {4} Relevant Clauses... Uses [0 min, 1.45
7 sec]

>>> Start Running {COREF} Operator of {tcoref(wordid1, wordid2)} with {4} Relevant Clauses
>>> {{COREF} Operator of {tcoref(wordid1, wordid2)} with {4} Relevant Clauses} uses [0 min, 38.860 sec]
>>> Dumping results for tcoref(wordid1, wordid2)

>>> Optimize DMOs for {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {
label(seqid1, wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 2}... Uses [0 min, 9.877 sec]

>>> Optimize DMOs for {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {
label(seqid1, wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 1}... Uses [0 min, 2.484 sec]

>>> Optimize DMOs for {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {
label(seqid1, wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 3}... Uses [0 min, 2.459 sec]

>>> Optimize DMOs for {LR} Operator of {label(seqid1, wordid2, label3)} with {3} Relevant Clauses Partitioned by: {
label(seqid1, wordid2, label3)=(round((seqid1 * 1.0)) % 4) = 0}... Uses [0 min, 2.232 sec]
```

Figure 4: Screencast of Felix

5 Input Options

5.1 Local Files

This is the standard way to input data to Felix. Supply MLN program files with -i and evidence files with -e. See Figures 1 and 2 for examples.

5.2 Relational Database Tables

Another option for supplying evidence to Felix is through relational database tables. To use this option, first edit the predicate declaration in the MLN program file to specify the name of the relational database table.

```
*word(seqid, wordid, word) <~db~ my_schema/my_table
```

In this example, the predicate "word" is supplied via the relational database table "my_table" in schema "my_schema". The database table also needs to follow several Felix specific options before it can be used. Each table requires two columns. The first column must be named "truth" with type boolean. The value of this column specifies whether each tuple is true or false. The second required column must be named "prior" with type real or double. The value of this column specifies the probability of each tuple. The predicate arguments also need to follow some conventions. For each predicate argument, the database table needs a column starting with the type of the argument followed by the argument index starting at 1. The type of each predicate argument column must be string unless the argument is specified with the "double_" or "int_" option.

```
 truth | prior | seqid1 | wordid2 | word3
```

5.3 BlahBlah feature extraction language

The final option for supplying evidence to Felix is through its feature extraction language called BlahBlah. BlahBlah makes use of Hadoop and Python to easily extract features from unstructured and semi-structured data on HDFS.

To use this option, first edit the predicate declaration in the MLN program file. The first line is similar to using a relational database table. However instead of a schema and table, a filepath on HDFS is specified. See Figures 5 and 6 for example programs.

Within the predicate declaration there can be three Felix functions containing arbitrary python code:

@MAPINIT This function can be used for initializing variables or importing packages. Code here will only be run once on each node in the Hadoop cluster. This function is optional.

@MAP This function contains the Map code. For XML files, use "<xml tag>" where tag is name of the XML tag which contains relevant data. Use "felixio_collect" to generate data to be used in the Reduce function. This function is required.

@REDUCE This function contains the Reduce code. It combines the data generated by the Map function and outputs it in the format specified by the predicate declaration with "felixio_push". The number of arguments sent to "felixio_push" should be exactly the same with the target relation – each invocation of "felixio_push" will generate a tuple in the target relation. This function is optional. If not specified, Felix will use a default reducer which will output each key, value pair generated by the mapper. Please note that the default reducer can only be used for predicates with exactly two arguments.

Notes

- Python packages: Currently, Felix allows all python packages included in Jython's original "Lib" folder to be imported.
- Third-party java code/packages: Arbitrary java code/packages can be run following Jython's grammar.
- Debugging: Use the **-local** option for debugging feature extraction programs. Doing so displays output from print statements.

Required Options (See Section 6 for details)

- **-auxSchema**
- **-hdfs**
- **-mapreduce**
- **-nReduce**

6 Command Options

Felix has several options on top of what Tuffy has:

- **-auxSchema**: Schema used for saving BlahBlah results.
- **-dd**: Run in dual decomposition mode.
- **-explain**: Print out the execution plan of Felix without actually executing the program.
- **-gp**: Use Greenplum instead of PostgreSQL.
- **-hdfs**: HDFS address (e.g., hdfs://localhost:9000).
- **-local**: Connect to a local Hadoop. This is useful for debugging program files with print statements.
- **-mapreduce**: MapReduce address (e.g., hdfs://localhost:9001).
- **-nDD**: Number of iterations in dual decomposition.
- **-nReduce**: Number of reducers to use in Hadoop.

```
*WordCount(word, count) <~hdfs~ hdfs://localhost:9000/my_directory/my_file.xml
{

@MAPINIT {
  import re
}@

@MAP <xml title> on inputv{
  for m in re.finditer('<title>(.*?)</title>', inputv):
    title = m.group(1)
    for k in title.split(' '):
      felixio_collect(k, '1')
}@

@REDUCE on (key, values){
  sum = 0
  for v in values:
    sum = sum + int(v)
  felixio_push(key, sum)
}@

}

Popular(word)

WordCount(word, c), [c > 100]  => Popular(word).
```

Figure 5: Sample MLN program using BlahBlah (XML)

```
*WordLength(word, len) <~hdfs~ hdfs://localhost:9000/my_directory/my_file
{

@MAP on inputv{
  for m in inputv.split(' '):
    felixio_collect(m, len(m))
}@

}

LongWord(word)

WordLength(word, len), [len > 10]  => LongWord(word).
```

Figure 6: Sample MLN program using BlahBlah (text)

References

[1] P. Domingos and D. Lowd. Markov Logic: An Interface Layer for Artificial Intelligence. 2009. 2

[2] F. Niu, C. Zhang, C. Ré, and J. Shavlik. Felix: Scaling Inference for Markov Logic with an Operator-based Approach; `http://http://arxiv.org/abs/1108.0294v1`. *Technical Report*, 2011. 3

[3] M. Richardson and P. Domingos. Markov logic networks. *Machine Learning*, 2006. 2