

Párhuzamos R programok végrehajtása sparklyr segítségével az ELKH Cloud infrastruktúrán



Understanding the role of Apache Spark

in the big data ecosystem



Big Data

The theoretical approach

- a) Volume
- b) Variety
- c) Velocity



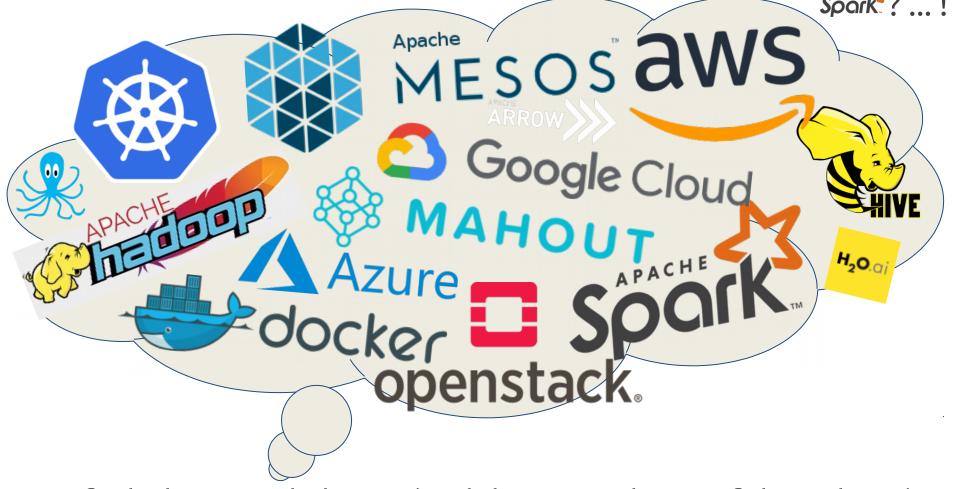
Big Data

The theoretical approach

- a) Volume
- b) Variety
- c) Velocity

The practical approach

- d) Doesn't fit
- e) Too slow



It can feel a bit overwhelming. (And this is just the tip of the iceberg.)



The type of statistical model

The **exact formula** being implemented

The way the **algorithm** works

The way **individual calculations** are computed

The way the distribution of the operations is achieved

The way the control of the distribution of the operations is achieved

Data distribution and I/O operations



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Pata distribution and I/O operations





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Pata distribution and I/O operations







The type of **statistica** This is the Spark Machine Learning Library

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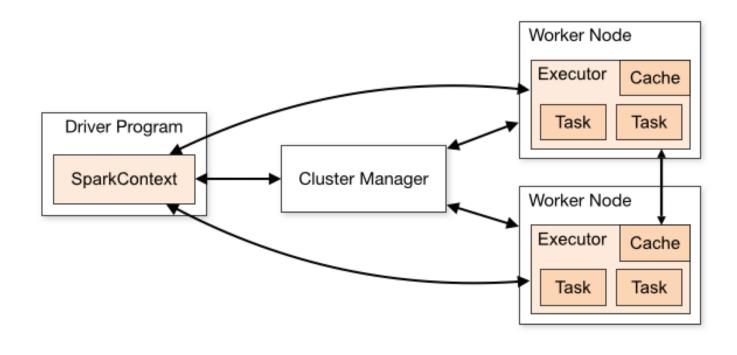


Apache Spark and Hadoop architectures

in a nutshell

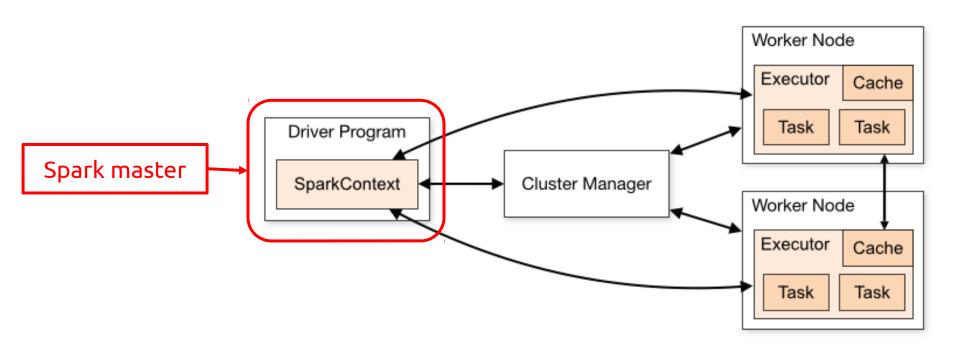






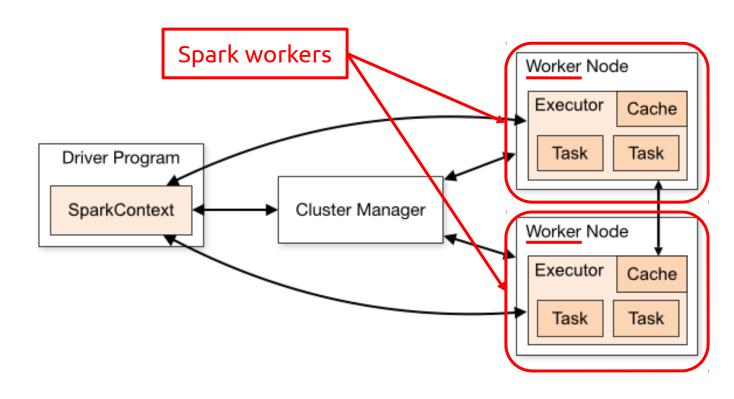






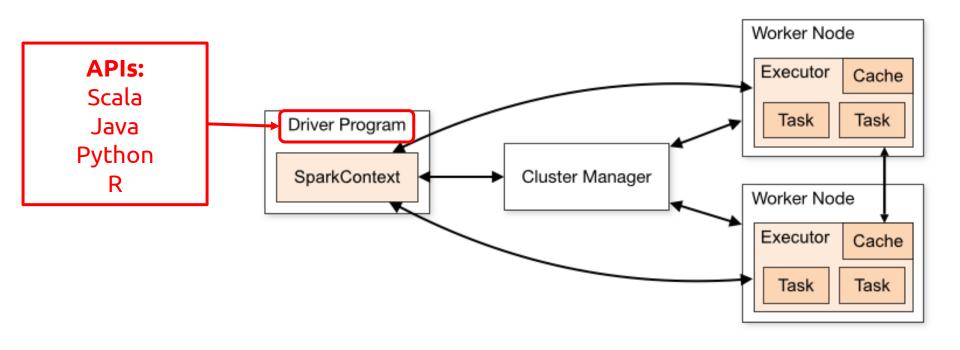


Spark architecture basics



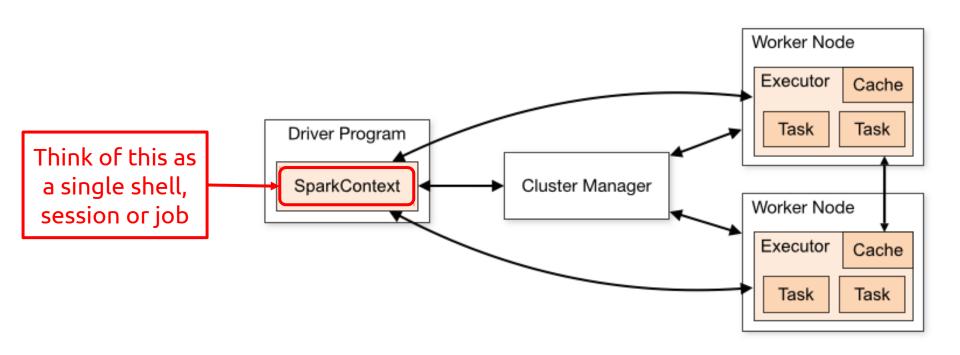












Spark architecture basics



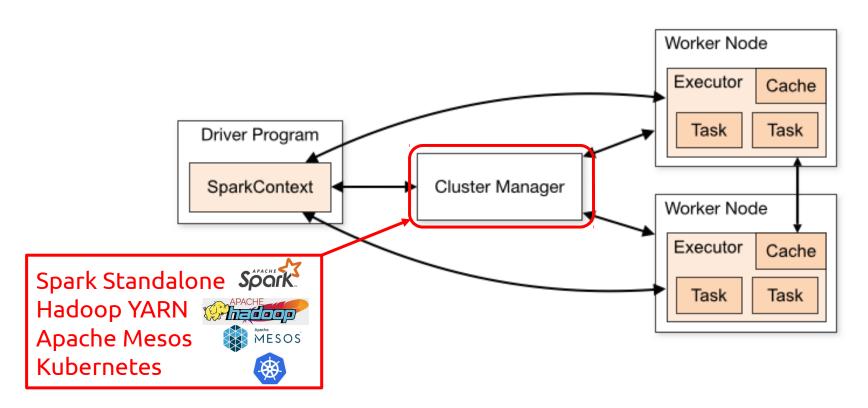


Image source and further details: https://spark.apache.org/docs/latest/cluster-overview.html

Spark architecture basics



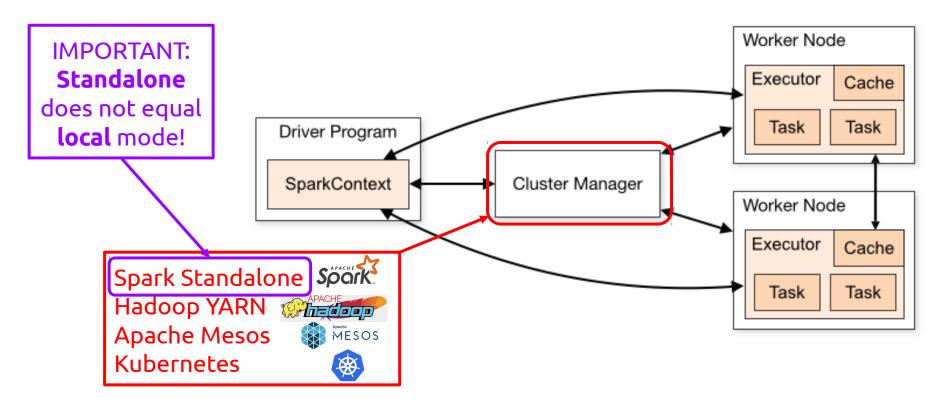


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Understanding Hadoop for Spark

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The way the distribution of the operations is achieved: Hadoop MapReduce

The way the control of the distribution of the operations: Hadoop YARN

Data distribution and I/O operations: Hadoop Distributed File System (HDFS)



Understanding Hadoop for Spark

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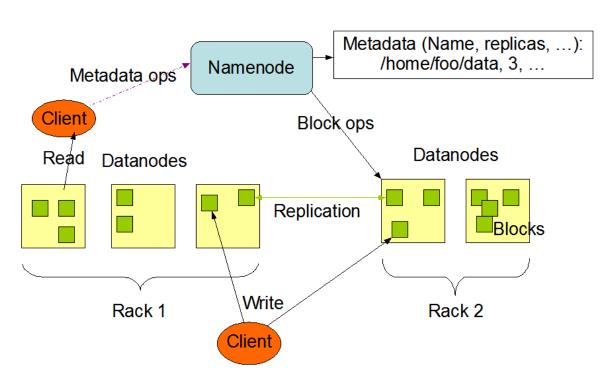
The way the control of the distribution of the operations: Hadoop YARN

Data distribution and I/O operations: Hadoop Distributed File System (HDFS)



The Hadoop Distributed File System (HDFS)

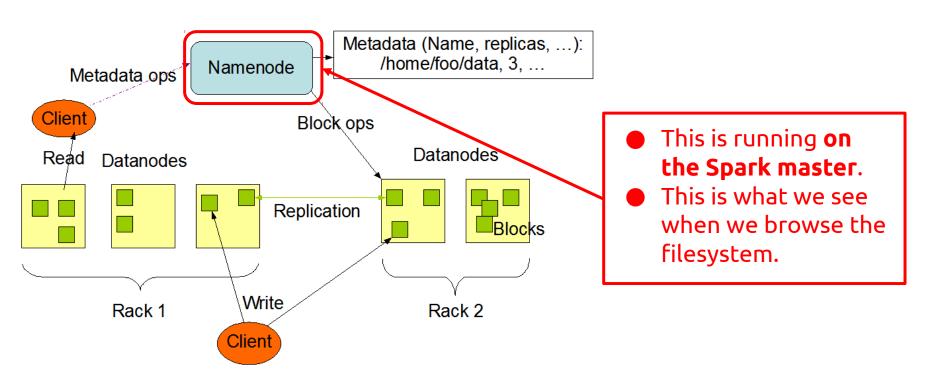
HDFS Architecture







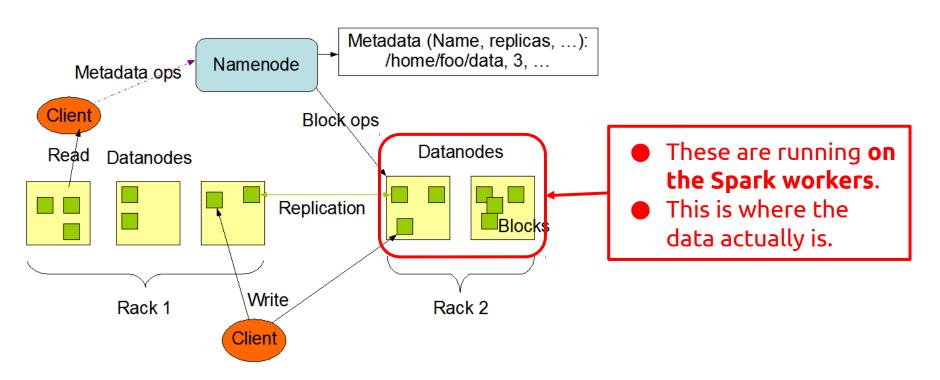
HDFS Architecture







HDFS Architecture



Data replication and fault tolerance in the HDFS

Block Replication

Namenode (Filename, numReplicas, block-ids, ...)
/users/sameerp/data/part-0, r:2, {1,3}, ...
/users/sameerp/data/part-1, r:3, {2,4,5}, ...

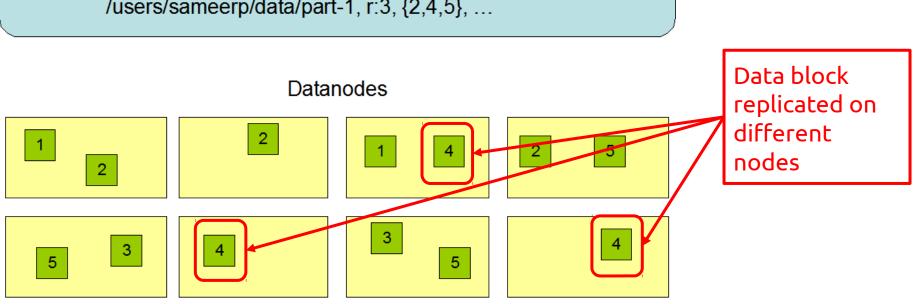
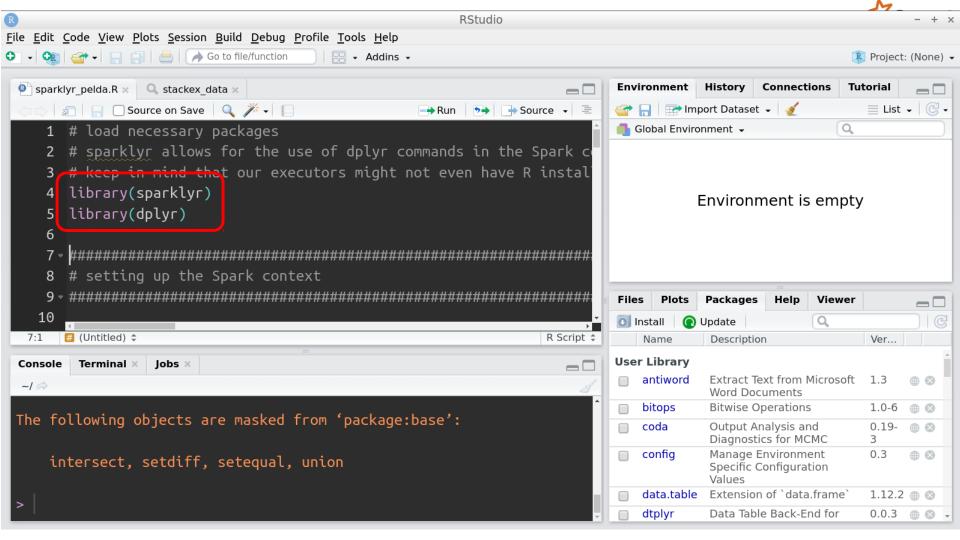


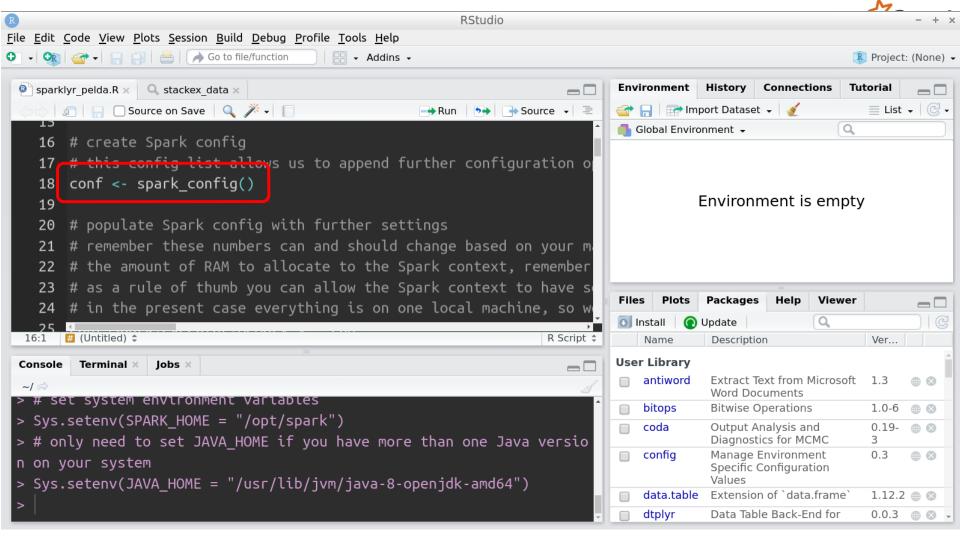
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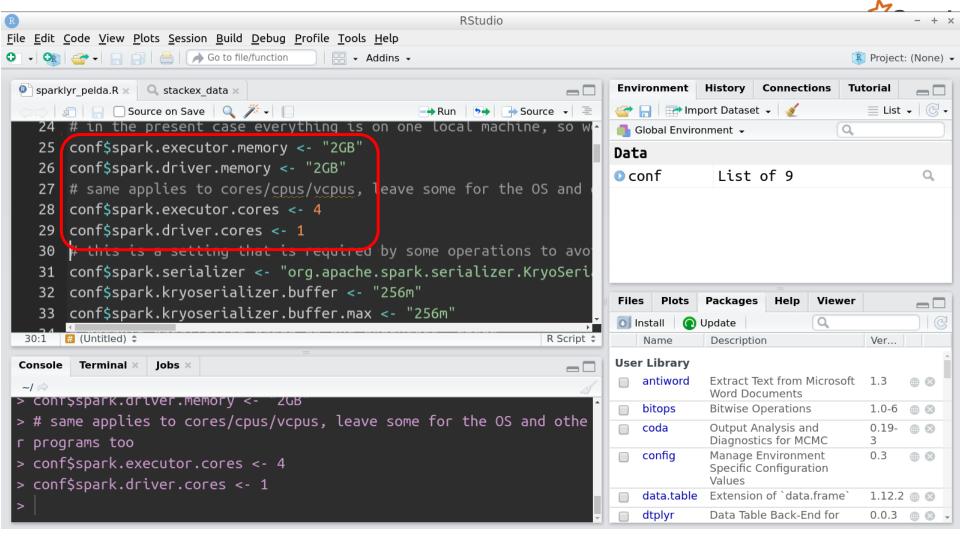


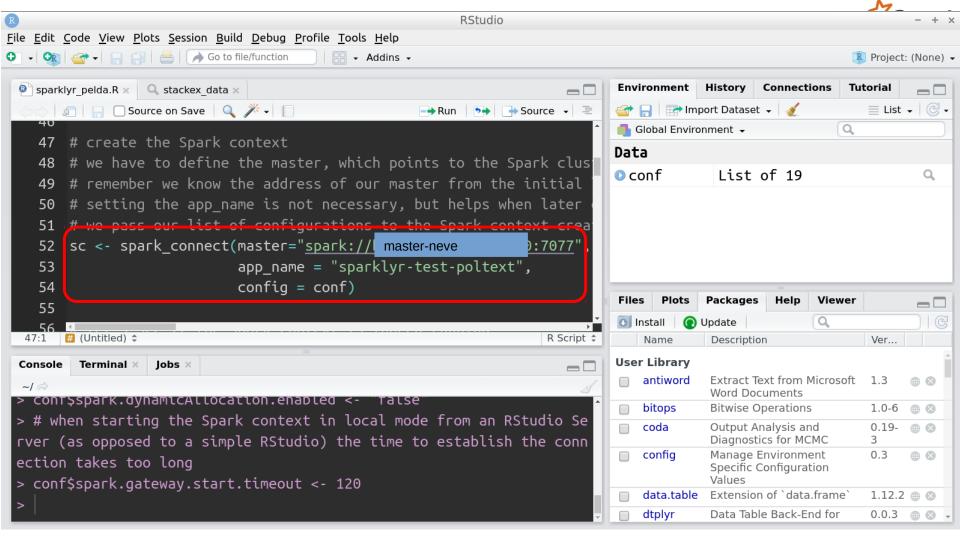
Let's get practical!

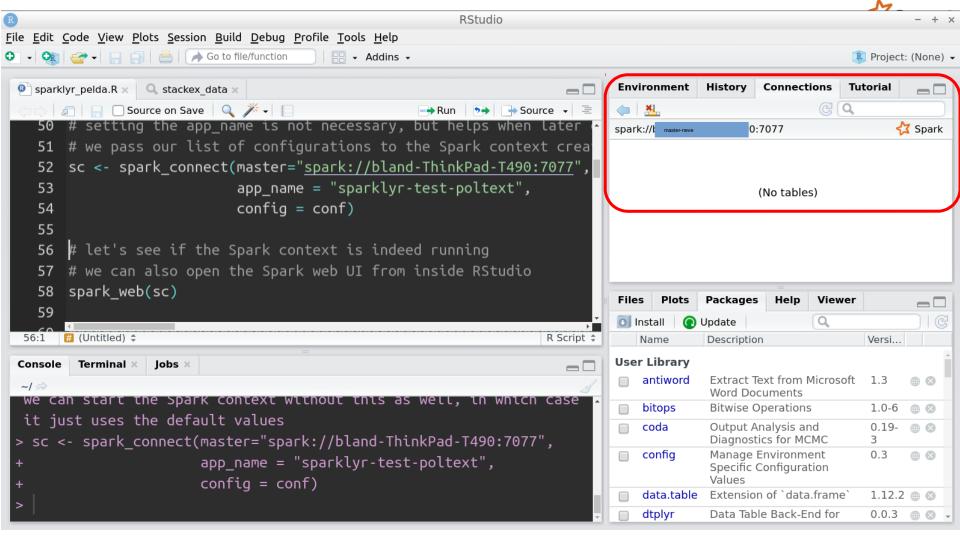
You can find all code and explanations at: https://github.com/zkpti/poltext2019-sparktutorial

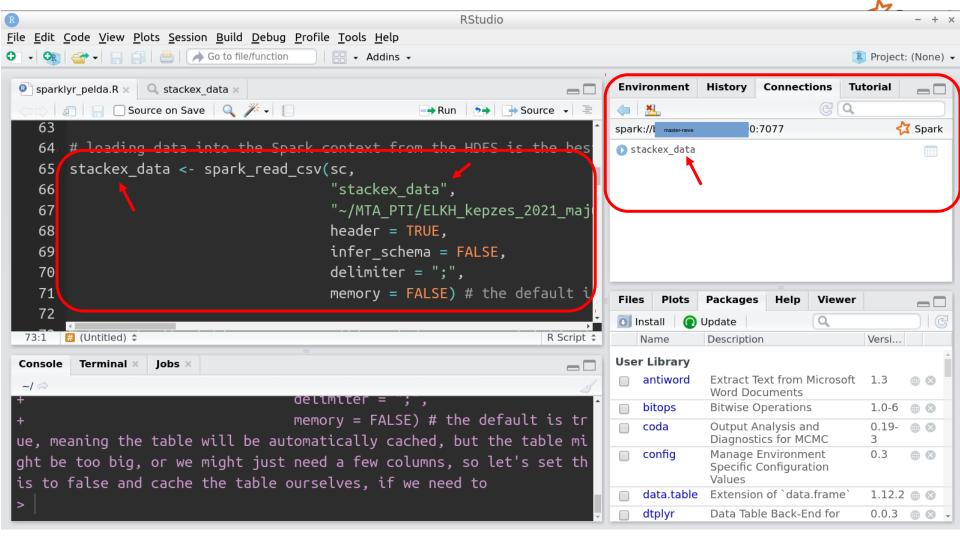


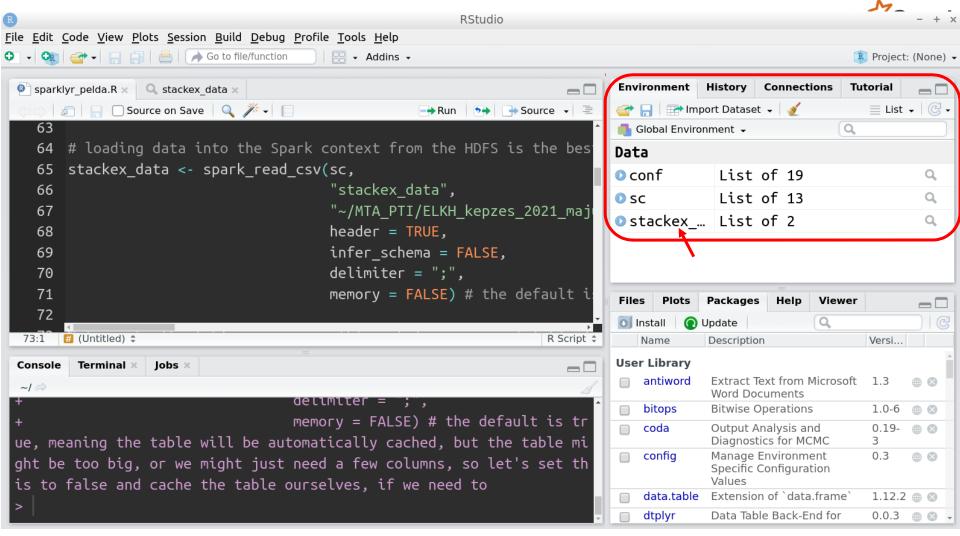


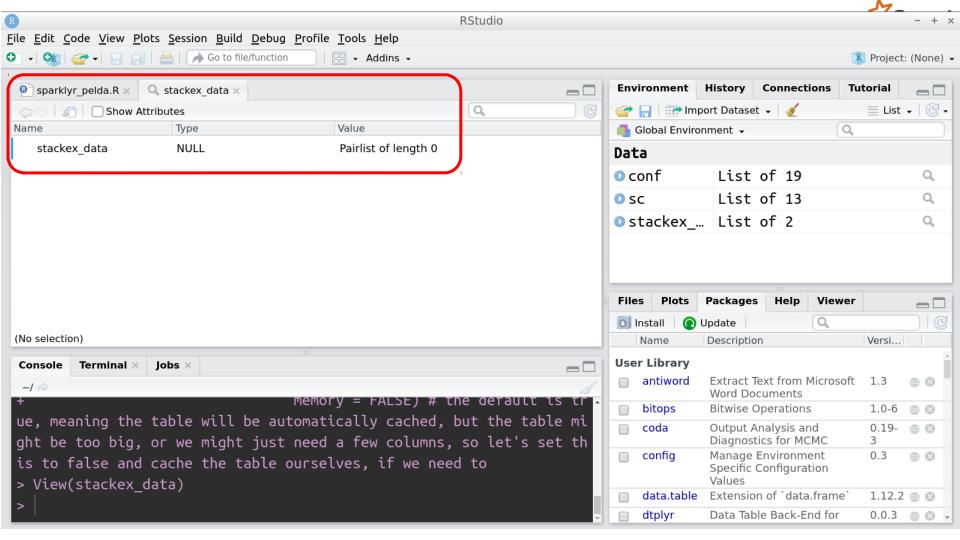


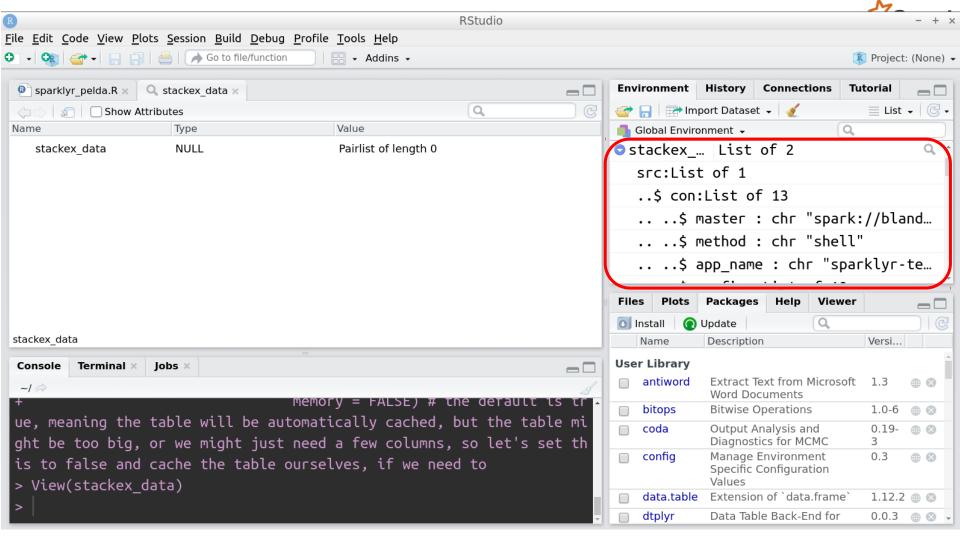


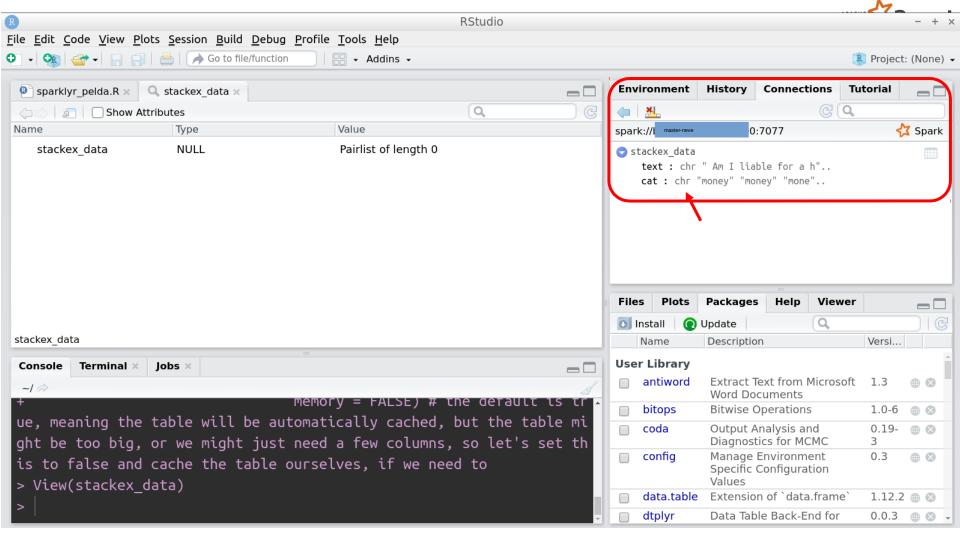


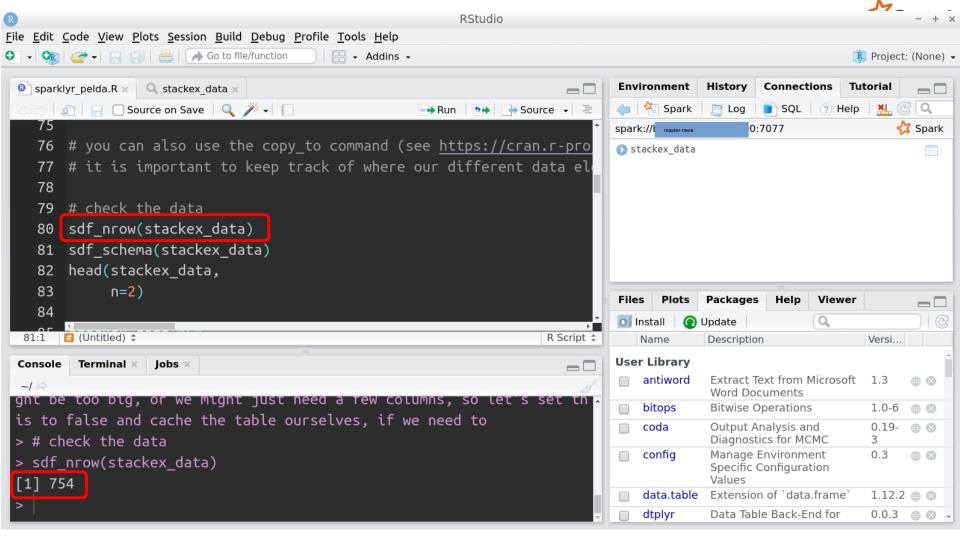


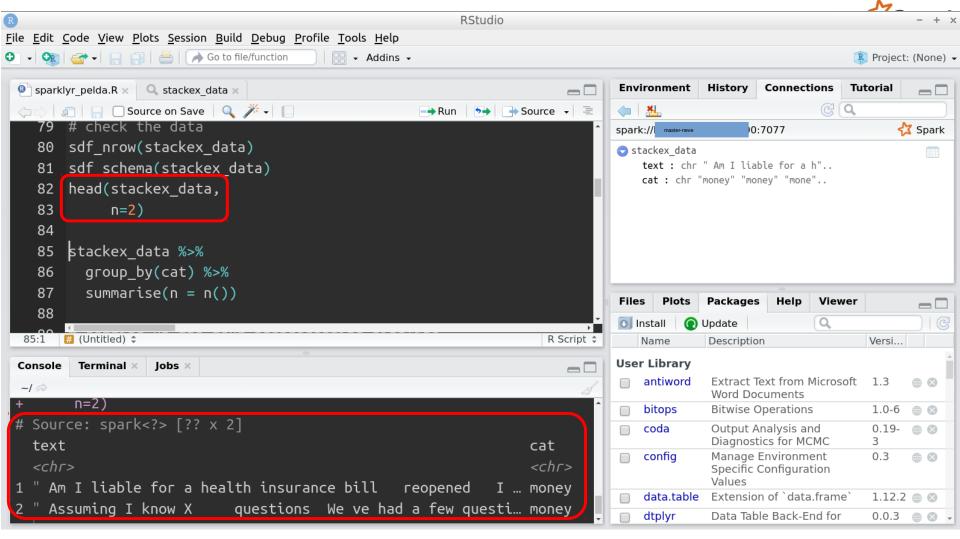


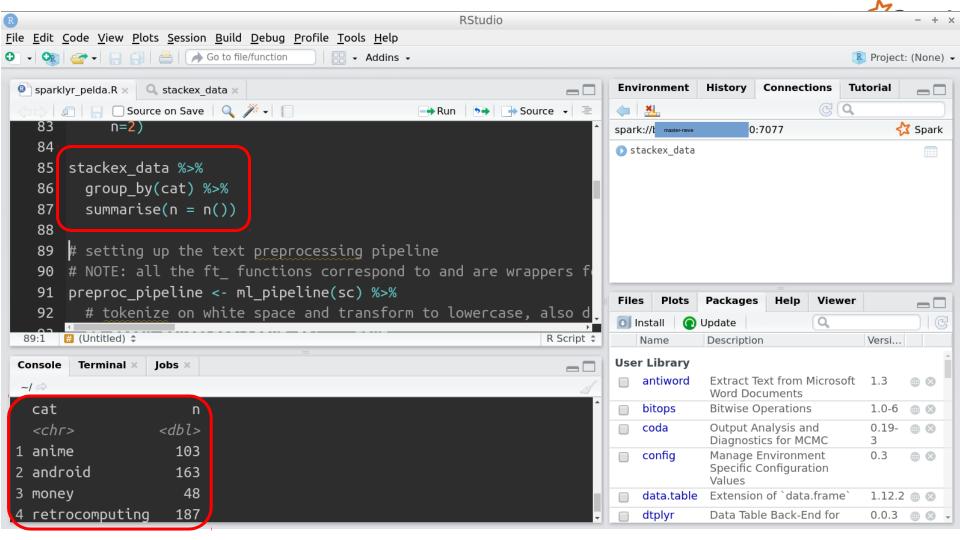


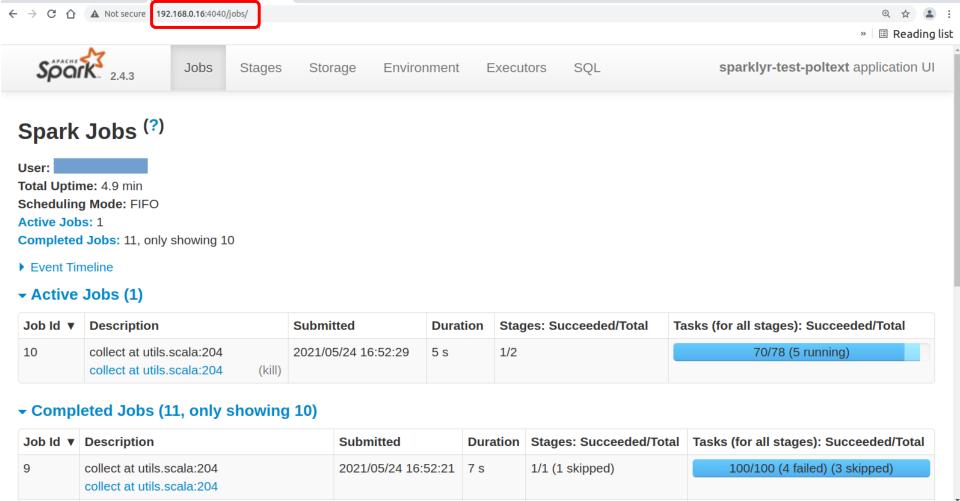




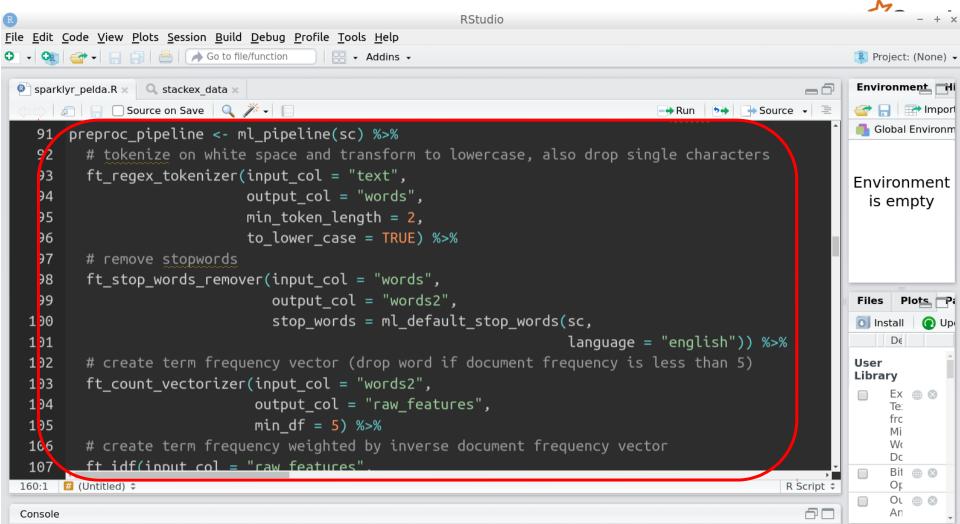








Spark Master at spar ×



```
104
                           output col = "raw features",
105
                           min df = 5) %>%
      # create term frequency weighted by inverse document frequency vector
106
       ft idf(input col = "raw features",
107
              output col = "features")
108
109
110
    # call pipeline to transform the data
    stackex data <- ml fit and transform(preproc pipeline,
111
112
                                           stackex data)
113
    # check the data again
114
    sdf nrow(stackex data)
115
```

sdf schema(stackex data)

head(stackex data,

n=2)

116

117

118

119



```
functions correspond to and are wrappers for Spark MLlib functions, jus
     nb pipeline <- ml pipeline(sc) %>%
122
123
       # have to change the text labels to numeric for the classifier to be able to handle it
124
       ft string indexer(input col = "cat",
125
                         output col = "label") %>%
       # add the naive bayes classifier to the pipeline
126
127
       ml naive bayes()
128
     # parameter grid for parameter tuning (this is very small and simple on purpose for the tu
129
     # the name of the list element that corresponds to a pipeline element (in this case "naive
130
     # you can add more than one parameter to tune at the same time, note how the parameter name
131
     param grid <- list(</pre>
132
133
       naive bayes = list(
134
         smoothing = c(1.0)
```

135

136

137)

0.5)



```
oss valldator for parameter tuning
    # note: the default metric for ml multiclass classification evaluator is f1, we could also
140
    # see https://cran.r-project.org/web/packages/sparklyr/sparklyr.pdf
141
    cv <- ml cross validator(sc,</pre>
142
143
                               estimator = nb pipeline,
144
                               estimator param maps = param grid,
145
                               evaluator = ml multiclass classification evaluator(sc),
146
                               num folds = 3,
147
                               parallelism = 4 # this is based on the number of cores/cpus/vcpus
148
149
     # create train-test solit
150
     split data <- sdf random split(stackex data,</pre>
151
152
                                     training = 0.7,
153
                                     test = 0.3
```



```
156
                                 ml fit and transform, but here we just need our model, so we
157
     cv model <- ml fit(cv,
158
                        split data$training)
159
160
     # check the metrics of the parameter tuning results
161
     ml validation metrics(cv model)
162
163
     # apply model to the test set (now we call only ml_transform, since our model is already f
164
     test with pred <- ml transform(cv model,
165
                                    split data$test)
166
167
     # check evaluation metrics for the test set
168
     ml multiclass classification evaluator(test with pred,
```

label col = "label",

metric name = "f1")

prediction col = "prediction",

169

170

171



```
# since this can be too much to handle, let's just collect the columns we need for now
193
     test with pred redux <- select(test with pred,
194
195
                                     cat,
196
                                     pred cat)
     test df <- sdf collect(test with pred redux)</pre>
197
198
199
     install.packages("tidyr") # we need this for the spread function
     library(tidyr)
200
201
```

now we can use the spread function on our dataframe in the R session to create the con

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204

205

206

207

208

test df %>%

group by(cat,

pred cat) %>%

summarise(n = n()) %>%

value = n)

spread(key = cat,



```
214
     # (just as it is important to keep track of where our data is, it is also important to kee
215
     test with pred %>%
216
       group by(cat,
                pred cat) %>% (# this happens in the Spark context
217
218
       summarise(n = n()) \% > \% # this happens in the Spark context
219
      collect() %>%
                            # this is where we move our data from the Spark context to the R
220
       spread(key = cat,
221
              value = n)
                               # this happens in the R session
```

```
test_with_pred %>%
filter(label != 0) %>%
ml_multiclass_classification_evaluator(label_col = "label",
prediction_col = "prediction",
metric name = "f1")
```

let's try the linear SVC model

hmmm, maybe we should check our metrics without the gardening category

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229

230 #



Thank you for your attention!

You can find all code and explanations at: https://github.com/zkpti/poltext2019-sparktutorial