### Benchmark based on the WiLI dataset

The *fastText* language identification pre-trained models support currently 176 languages. The following character vector shows the available *language isocodes*.

```
fasttext_supported_languages = c('af', 'als', 'am', 'an', 'ar', 'arz',
'as', 'ast', 'av',
                                 'az', 'azb', 'ba', 'bar', 'bcl', 'be',
'bg', 'bh', 'bn',
                                 'bo', 'bpy', 'br', 'bs', 'bxr', 'ca',
'cbk', 'ce', 'ceb',
                                 'ckb', 'co', 'cs', 'cv', 'cy', 'da',
'de', 'diq', 'dsb',
                                 'dty', 'dv', 'el', 'eml', 'en', 'eo',
'es', 'et', 'eu',
                                 'fa', 'fi', 'fr', 'frr', 'fy', 'ga',
'gd', 'gl', 'gn',
                                 'gom', 'gu', 'gv', 'he', 'hi', 'hif',
'hr', 'hsb', 'ht',
                                 'hu', 'hy', 'ia', 'id', 'ie', 'ilo',
'io', 'is', 'it',
                                 'ja', 'jbo', 'jv', 'ka', 'kk', 'km',
'kn', 'ko', 'krc',
                                 'ku', 'kv', 'kw', 'ky', 'la', 'lb',
'lez', 'li', 'lmo',
                                 'lo', 'lrc', 'lt', 'lv', 'mai', 'mg',
'mhr', 'min', 'mk',
                                 'ml', 'mn', 'mr', 'mrj', 'ms', 'mt',
'mwl', 'my', 'myv',
                                 'mzn', 'nah', 'nap', 'nds', 'ne',
'new', 'nl', 'nn', 'no',
                                 'oc', 'or', 'os', 'pa', 'pam', 'pfl',
'pl', 'pms', 'pnb',
                                 'ps', 'pt', 'qu', 'rm', 'ro', 'ru',
'rue', 'sa', 'sah',
                                 'sc', 'scn', 'sco', 'sd', 'sh', 'si',
'sk', 'sl', 'so',
                                 'sq', 'sr', 'su', 'sv', 'sw', 'ta',
'te', 'tg', 'th', 'tk',
                                 'tl', 'tr', 'tt', 'tyv', 'ug', 'uk',
'ur', 'uz', 'vec',
                                 'vep', 'vi', 'vls', 'vo', 'wa', 'war',
'wuu', 'xal', 'xmf',
                                 'yi', 'yo', 'yue', 'zh')
```

For illustration purposes we'll subset the *WiLI dataset* to the 2-letter isocodes of the supported fastText languages. For this purpose we'll use the ISOcodes R package and especially the **ISO_639_2** function which includes the required 2- and 3-letter isocodes and also the available full names of the languages,

```
isocodes = ISOcodes::ISO_639_2
# head(isocodes)

comp_cases = complete.cases(isocodes$Alpha_2)
isocodes_fasttext = isocodes[comp_cases, ]
# dim(isocodes_fasttext)

idx_keep_fasttext = which(isocodes_fasttext$Alpha_2 %in%
fasttext_supported_languages)

isocodes_fasttext = isocodes_fasttext[idx_keep_fasttext, ]
isocodes_fasttext = data.table::data.table(isocodes_fasttext)
# isocodes_fasttext

lower_nams = tolower(isocodes_fasttext$Name)
lower_nams = trimws(as.vector(unlist(lapply(strsplit(lower_nams, "[;,
]"), function(x) x[1]))), which = 'both')   # remove second or third
naming of the country name

isocodes_fasttext$Name_tolower = lower_nams
isocodes_fasttext
```

```
##      Alpha_3_B Alpha_3_T Alpha_2      Name Name_tolower
##   1:       afr       afr      af Afrikaans    afrikaans
##   2:       alb       sqi      sq  Albanian     albanian
##   3:       amh       amh      am   Amharic      amharic
##   4:       ara       ara      ar    Arabic       arabic
##   5:       arg       arg      an Aragonese    aragonese
##  ---
## 118:       vol       vol      vo   Volapük      volapük
## 119:       wel       cym      cy     Welsh        welsh
## 120:       wln       wln      wa   Walloon      walloon
## 121:       yid       yid      yi   Yiddish      yiddish
## 122:       yor       yor      yo    Yoruba       yoruba
```

The next function will be used to compute and print the accuracy in all cases,

```
print_accuracy = function(size_input_data,
                          true_data,
                          preds_data,
                          method) {

  cat(glue::glue("Total Rows: {size_input_data}"), '\n')
  rnd_2 = round(length(preds_data)/size_input_data, 4)
  msg_2 ="Predicted Rows: {length(preds_data)}  ({rnd_2 * 100}%
predicted)"
  cat(glue::glue(msg_2), '\n')
  cat(glue::glue("Missing Values:  {size_input_data -
length(preds_data)}"), '\n')
  rnd_4 = round(sum(true_data == preds_data) / length(preds_data), 4)
  msg_4 = "Accuracy on 'Predicted Rows' using '{method}':  {rnd_4 *
100}%"
```

```
  cat(glue::glue(msg_4), '\n')
}

# fasttext language identification supported languages as described in
```
https://fasttext.cc/docs/en/language-identification.html

As mentioned earlier the *WiLI benchmark dataset* can be downloaded either from Zenodo or from my Datasets Github repository. Once downloaded and unzipped the folder includes the following files (for the remaining of this blog post I'll assume that the **dir_wili_2018** variable points to the *WiLI* data directory ),

```
list.files(dir_wili_2018)
```

```
## [1] "labels.csv"  "lid.176.bin" "README.txt"  "urls.txt"    "x_test.txt"
## [6] "x_train.txt" "y_test.txt"  "y_train.txt"
```

For this benchmark we'll use only the **test** data ('x_test.txt' and 'y_test.txt' files) and we'll keep only the *WiLI-isocodes* that intersect with the *fastText isocodes*,

```
## Initial observations:  117500  Subset based on isocodes:  50500   Number of languages based
on subset:  101
```

```
##     V1
## 1: ava
## 2: mon
## 3: bul
## 4: ido
## 5: ara
## 6: kan
```

### fastText based on the smaller pre-trained model 'lid.176.ftz' (approx. 917 kB)

First, we'll use the smaller pre-trained dataset,

```
file_ftz = system.file("language_identification/lid.176.ftz", package =
"fastText")

dtbl_res_in = fastText::language_identification(input_obj =
wili_test_x$V1,

pre_trained_language_model_path = file_ftz,
                                                      k = 1,
                                                      th = 0.0,
                                                      threads = 1,
                                                      verbose = TRUE)
```

```
## The 'fasttext' algorithm starts ...
## The predicted labels will be loaded from the temporary file ...
## The temporary files will be removed ...
## Elapsed time: 0 hours and 0 minutes and 5 seconds.
```

```
dtbl_res_in$true_label = wili_test_y$V1
# dtbl_res_in

isocodes_fasttext_subs = isocodes_fasttext[, c(1,3)]   # merge the
predicted labels with the 3-letter isocodes

merg_labels = merge(dtbl_res_in, isocodes_fasttext_subs, by.x =
'iso_lang_1', by.y = 'Alpha_2')
# as.vector(colSums(is.na(merg_labels)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = merg_labels$true_label,
               preds_data = merg_labels$Alpha_3_B,
               method = 'fastText (.ftz pre-trained model)')
```

```
## Total Rows: 50500
## Predicted Rows: 50211  (99.43% predicted)
## Missing Values:  289
## Accuracy on 'Predicted Rows' using 'fastText (.ftz pre-trained model)':  83.05%
```

The **accuracy** of the model was **83.05%** (on **50211** out of **50500** text extracts)

### fastText based on the bigger pre-trained model 'lid.176.bin' (approx. 126 MB)

Let's move to the bigger pre-trained model which is mentioned to be more accurate. This model can be downloaded either from the official website or from my Datasets Github repository. The parameter setting of the **fastText::language_identification()** function is the same as before, and the only thing that changes is the **pre_trained_language_model_path** parameter which is set to **lid.176.bin**. Assuming this file is downloaded and extracted in the **dir_wili_2018** directory then,

```
file_bin = file.path(dir_wili_2018, 'lid.176.bin')

dtbl_res_in = fastText::language_identification(input_obj =
wili_test_x$V1,

pre_trained_language_model_path = file_bin,
                                                 k = 1,
                                                 th = 0.0,
                                                 threads = 1,
                                                 verbose = TRUE)
```

```
## The 'fasttext' algorithm starts ...
## The predicted labels will be loaded from the temporary file ...
## The temporary files will be removed ...
## Elapsed time: 0 hours and 0 minutes and 5 seconds.
```

```
dtbl_res_in$true_label = wili_test_y$V1
# dtbl_res_in

isocodes_fasttext_subs = isocodes_fasttext[, c(1,3)]   # merge the
predicted labels with the 3-letter isocodes

merg_labels = merge(dtbl_res_in, isocodes_fasttext_subs, by.x =
'iso_lang_1', by.y = 'Alpha_2')
# as.vector(colSums(is.na(merg_labels)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = merg_labels$true_label,
               preds_data = merg_labels$Alpha_3_B,
               method = 'fastText (.ftz pre-trained model)')
```

```
## Total Rows: 50500
## Predicted Rows: 50168  (99.34% predicted)
## Missing Values:  332
## Accuracy on 'Predicted Rows' using 'fastText (.ftz pre-trained model)':  86.55%
```

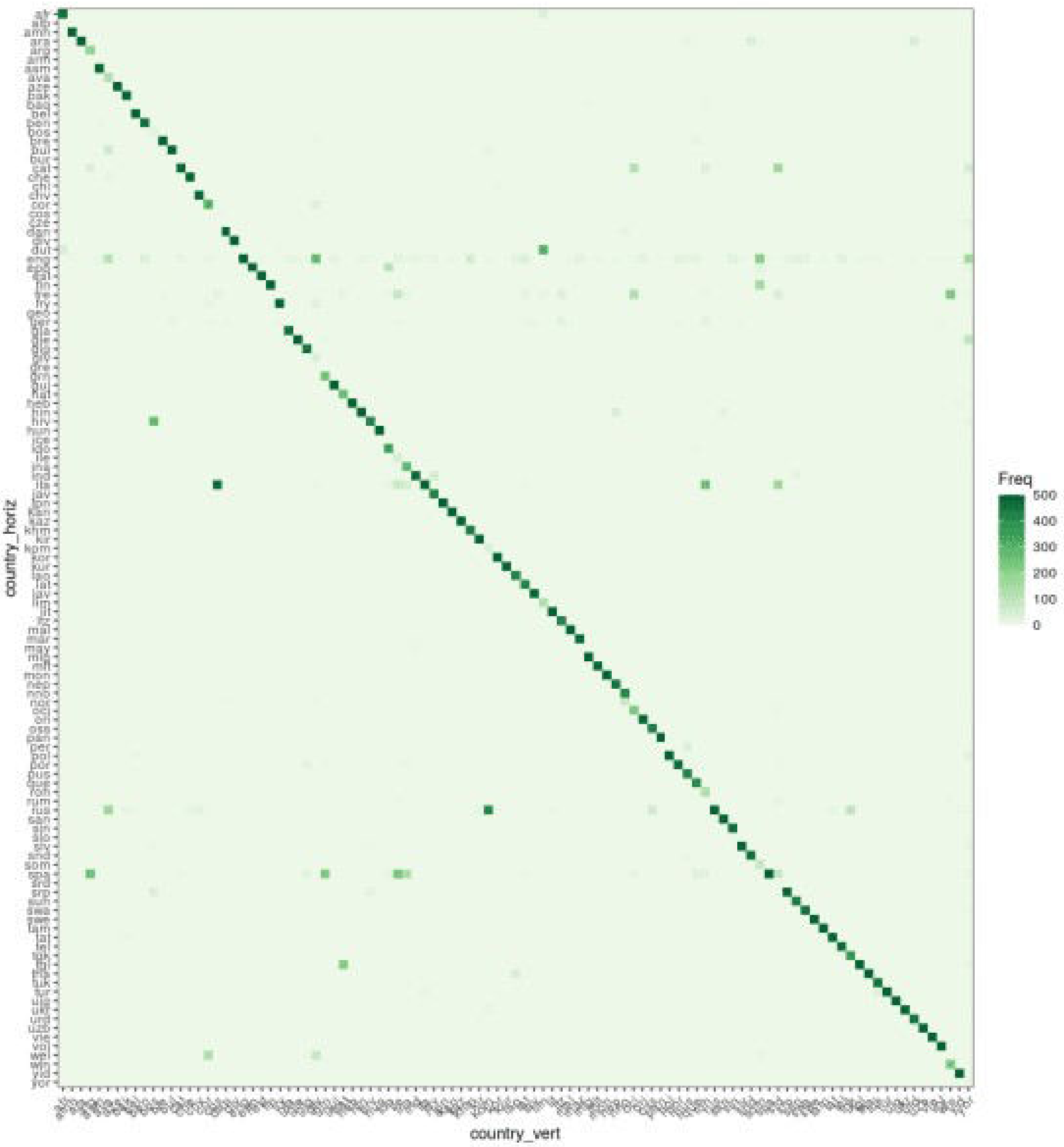
The **accuracy** based on the bigger model was increased to **86.55%** (on **50168** out of **50500** text extracts)

## ggplot visualization of the bigger .bin model

The following plot shows the confusion matrix of the bigger .bin model. The main diagonal is dominated by the dark green color indicating higher accuracy rates,

```
tbl = table(merg_labels$true_label, merg_labels$Alpha_3_B)

df = as.data.frame.table(tbl)
colnames(df) = c('country_vert', 'country_horiz', 'Freq')
# head(df)

require(magrittr)
require(dplyr)
require(ggplot2)

df <- df %>%
  mutate(country_vert = factor(country_vert),                  #
alphabetical order by default
```

```
         country_horiz = factor(country_horiz, levels =
rev(unique(country_horiz))))

plt_tbl = ggplot(df, aes(x=country_vert, y=country_horiz, fill=Freq)) +
  geom_tile() + theme_bw() + coord_equal() +
  scale_fill_distiller(palette="Greens", direction=1) +
  ggplot2::theme(axis.text.x = element_text(angle = 45, vjust = 1.0,
hjust = 1.0))

plt_tbl
```




## ‘cld2’ language recognition package

The **Google’s Compact Language Detector 2** (CLD2) “ … probabilistically detects over 80 languages in Unicode UTF-8 text, either plain text or HTML/XML. For mixed-language input, CLD2 returns the top three languages found and their approximate percentages of the total text bytes (e.g. 80% English and 20% French out of 1000 bytes) …”. Based on the R package documentation, “The function ‘detect_language()’ is vectorised and guesses the language of each string in text or returns NA if the language could not reliably be determined.”

```
require(cld2)

t_start = proc.time()
cld2_vec = cld2::detect_language(text = wili_test_x$V1, plain_text =
TRUE, lang_code = TRUE)

cld2_dtbl = data.table::setDT(list(Alpha_2 = cld2_vec))
cld2_dtbl$true_label = wili_test_y$V1

merg_labels_cld2 = merge(cld2_dtbl, isocodes_fasttext_subs, by =
'Alpha_2')
# as.vector(colSums(is.na(merg_labels_cld2)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = merg_labels_cld2$true_label,
               preds_data = merg_labels_cld2$Alpha_3_B,
               method = 'cld2')
```

```
## Total Rows: 50500
## Predicted Rows: 34254  (67.83% predicted)
## Missing Values:  16246
## Accuracy on 'Predicted Rows' using 'cld2':  83.13%
```

```
## Elapsed time: 0 hours and 0 minutes and 1 seconds.
```

The **accuracy** of the **cld2** package is **83.13%** (on **34254** out of **50500** text extracts)

## ‘cld3’ language recognition package

The “ … Google’s Compact Language Detector 3 is a neural network model for language identification and the successor of CLD2 (available from) CRAN. This version is still experimental and uses a novell algorithm with different properties and outcomes. For more information see: https://github.com/google/cld3#readme …”. Based on the R package documentation, “The function detect_language() is vectorised and guesses the language of each string in text or returns NA if the language could not reliably be determined.”

```
require(cld3)

t_start = proc.time()
cld3_vec = cld3::detect_language(text = wili_test_x$V1)

cld3_dtbl = data.table::setDT(list(Alpha_2 = cld3_vec))
cld3_dtbl$true_label = wili_test_y$V1
```

```
merg_labels_cld3 = merge(cld3_dtbl, isocodes_fasttext_subs, by =
'Alpha_2')
# as.vector(colSums(is.na(merg_labels_cld3)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = merg_labels_cld3$true_label,
               preds_data = merg_labels_cld3$Alpha_3_B,
               method = 'cld3')
```

```
## Total Rows: 50500
## Predicted Rows: 43560  (86.26% predicted)
## Missing Values:  6940
## Accuracy on 'Predicted Rows' using 'cld3':  74.74%
```

```
## Elapsed time: 0 hours and 0 minutes and 18 seconds.
```

The **accuracy** of the **cld3** package is **74.74%** (on **43560** out of **50500** text extracts)

## Language recognition using the ‘textcat’ R package

The ‘textcat’ R package performs ‘text categorization based on n-grams’. The documentation of the package mentions: “… TextCat (https://www.let.rug.nl/vannoord/TextCat/) is a Perl implementation of the Cavnarand Trenkle ‘N-Gram-Based Text Categorization’ technique by Gertjan van Noord which was subsequently integrated into SpamAssassin. It provides byte n-gram profiles for 74 ‘languages’ (more precisely, language/encoding combinations). The C library reimplementation libtextcat (https://software.wise-guys.nl/libtextcat/) adds one more non-empty profile.

- ‘TC_byte_profiles’ provides these byte profiles.
- ‘TC_char_profiles’ provides a subset of 56 character profiles obtained by converting the byte sequences to UTF-8 strings where possible.

The category ids are unchanged from the original, and give the full (English) name of the language, optionally combined the name of the encoding script. Note that ‘scots’ indicates Scots, the Germanic language variety historically spoken in Lowland Scotland and parts of Ulster, to be distinguished from Scottish Gaelic (named ‘scots_gaelic’ in the profiles), the Celtic language variety spoken in most of the western Highlands and in the Hebrides (see https://en.wikipedia.org/wiki/Scots_language) …”

Apart from the previous 2 mentioned TC-profiles the **ECIMCI_profiles** (26 profiles) also exists. In my benchmark I’ll use only the *‘TC_byte_profile’* (75 profiles) and *‘TC_char_profiles’* (56 profiles) as input to the **textcat()** function to compute the country names, which by default the *textcat()* function returns. I’ll wrap the function to **parallel::mclapply()** because I observed it returns the results faster using multiple threads (in my benchmark I used 8 threads).

**using the 'TC_byte_profiles'**

Before proceeding lets have a look to the available profiles,

```
threads = parallel::detectCores()
require(textcat)

names(textcat::TC_byte_profiles)
```

```
##  [1] "afrikaans"           "albanian"            "amharic-utf"
##  [4] "arabic-iso8859_6"    "arabic-windows1256"  "armenian"
##  [7] "basque"              "belarus-windows1251" "bosnian"
## [10] "breton"              "bulgarian-iso8859_5" "catalan"
## [13] "chinese-big5"        "chinese-gb2312"      "croatian-ascii"
## [16] "czech-iso8859_2"     "danish"              "dutch"
## [19] "english"             "esperanto"           "estonian"
## [22] "finnish"             "french"              "frisian"
## [25] "georgian"            "german"              "greek-iso8859-7"
## [28] "hebrew-iso8859_8"    "hindi"               "hungarian"
## [31] "icelandic"           "indonesian"          "irish"
## [34] "italian"             "japanese-euc_jp"     "japanese-shift_jis"
## [37] "korean"              "latin"               "latvian"
## [40] "lithuanian"          "malay"               "manx"
## [43] "marathi"             "middle_frisian"      "mingo"
## [46] "nepali"              "norwegian"           "persian"
## [49] "polish"              "portuguese"          "quechua"
## [52] "romanian"            "rumantsch"           "russian-iso8859_5"
## [55] "russian-koi8_r"      "russian-windows1251" "sanskrit"
## [58] "scots"               "scots_gaelic"        "serbian-ascii"
## [61] "slovak-ascii"        "slovak-windows1250"  "slovenian-ascii"
## [64] "slovenian-iso8859_2" "spanish"             "swahili"
## [67] "swedish"             "tagalog"             "tamil"
## [70] "thai"                "turkish"             "ukrainian-koi8_r"
## [73] "vietnamese"          "welsh"               "yiddish-utf"
```

What we want is that the initial *lowercase isocodes* intersect with the processed *TC_byte_profiles* so that the computation of the accuracy is correct,

```
## Isocode-Names:  121  TC_byte_profiles:  75  Intersected Names: 61
```

```
t_start = proc.time()
textc = as.vector(unlist(parallel::mclapply(1:length(wili_test_x$V1),
function(x) {
  textcat(x = wili_test_x$V1[x], p = textcat::TC_byte_profiles, method
= "CT")
}, mc.cores = threads)))
```

```
textc = as.vector(unlist(lapply(strsplit(textc, '-'), function(x)
x[1])))
textc = trimws(textc, which = 'both')

unique(textc)
```

```
##  [1] "chinese"       "italian"       "arabic"        "french"
##  [5] "japanese"      "indonesian"    "catalan"       "finnish"
##  [9] "german"        "korean"        "spanish"       "middle_frisian"
## [13] "english"       "irish"         "yiddish"       "malay"
## [17] "slovenian"     "breton"        "esperanto"     "rumantsch"
## [21] "amharic"       "manx"          "quechua"       "frisian"
## [25] "afrikaans"     "romanian"      "swahili"       "serbian"
## [29] "scots_gaelic"  "vietnamese"    "latvian"       "norwegian"
## [33] "tagalog"       "portuguese"    "swedish"       "danish"
## [37] "estonian"      "turkish"       "dutch"         "polish"
## [41] "scots"         "bosnian"       "hungarian"     "croatian"
## [45] "latin"         "lithuanian"    "marathi"       "welsh"
## [49] "basque"        "slovak"        "armenian"      "sanskrit"
## [53] "czech"         NA              "icelandic"     "bulgarian"
## [57] "albanian"      "thai"          "russian"       "tamil"
```

```
textc_dtbl = data.table::setDT(list(Name_tolower = textc))
textc_dtbl$true_label = wili_test_y$V1

fasttext_isoc_name = isocodes_fasttext[, c(1,5)]
merg_labels_textc = merge(textc_dtbl, fasttext_isoc_name, by =
'Name_tolower')
# as.vector(colSums(is.na(merg_labels_cld2)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = merg_labels_textc$true_label,
               preds_data = merg_labels_textc$Alpha_3_B,
               method = 'textcat ( TC_byte_profiles )')
```

```
## Total Rows: 50500
## Predicted Rows: 47324  (93.71% predicted)
## Missing Values:  3176
## Accuracy on 'Predicted Rows' using 'textcat ( TC_byte_profiles )':  29.91%
```

```
## Elapsed time: 0 hours and 1 minutes and 20 seconds.
```

The **accuracy** of the **textcat** package using the **TC_byte_profiles** is **29.91%** (on **47324** out of **50500** text extracts)

**using the ‘TC_char_profiles’**

Again, as previously we can have a look to the available profiles,

```
names(textcat::TC_char_profiles)
```

```
##  [1] "afrikaans"            "albanian"             "basque"
##  [4] "belarus-windows1251"  "bosnian"              "breton"
##  [7] "bulgarian-iso8859_5"  "catalan"              "croatian-ascii"
## [10] "czech-iso8859_2"      "danish"               "dutch"
## [13] "english"              "esperanto"            "estonian"
## [16] "finnish"              "french"               "frisian"
## [19] "german"               "greek-iso8859-7"      "hebrew-iso8859_8"
## [22] "hungarian"            "icelandic"            "indonesian"
## [25] "irish"                "italian"              "latin"
## [28] "latvian"              "lithuanian"           "malay"
## [31] "manx"                 "middle_frisian"       "nepali"
## [34] "norwegian"            "polish"               "portuguese"
## [37] "romanian"             "rumantsch"            "russian-iso8859_5"
## [40] "russian-koi8_r"       "russian-windows1251"  "sanskrit"
## [43] "scots"                "scots_gaelic"         "serbian-ascii"
## [46] "slovak-ascii"         "slovak-windows1250"   "slovenian-ascii"
## [49] "slovenian-iso8859_2"  "spanish"              "swahili"
## [52] "swedish"              "tagalog"              "turkish"
## [55] "ukrainian-koi8_r"     "welsh"
```

What we want is that the initial *lowercase isocodes* intersect with the processed *TC_char_profiles* so that the computation of the accuracy is correct,

```
## Isocode-Names:  121  TC_char_profiles:  56  Intersected Names: 46
```

```
t_start = proc.time()
textc = as.vector(unlist(parallel::mclapply(1:length(wili_test_x$V1),
function(x) {
  textcat(x = wili_test_x$V1[x], p = textcat::TC_char_profiles, method
= "CT")
}, mc.cores = threads)))

textc = as.vector(unlist(lapply(strsplit(textc, '-'), function(x)
x[1])))
textc = trimws(textc, which = 'both')

unique(textc)
```

```
## [1] "belarus"      "russian"      "bulgarian"      "italian"
## [5] "polish"       "turkish"      "french"         "nepali"
## [9] "slovak"       "indonesian"   "sanskrit"       "catalan"
## [13] "icelandic"   "finnish"      "middle_frisian" "spanish"
## [17] "english"     "irish"        "hebrew"         "basque"
## [21] "afrikaans"   "malay"        "slovenian"      "esperanto"
## [25] "scots_gaelic" "breton"      "rumantsch"      "tagalog"
## [29] "manx"        "scots"        "frisian"        "romanian"
## [33] "swahili"     "lithuanian"   NA               "serbian"
## [37] "latvian"     "german"       "norwegian"      "czech"
## [41] "portuguese"  "swedish"      "danish"         "estonian"
## [45] "dutch"       "ukrainian"    "bosnian"        "latin"
## [49] "hungarian"   "croatian"     "welsh"          "albanian"
## [53] "greek"
```

```
textc_dtbl = data.table::setDT(list(Name_tolower = textc))
textc_dtbl$true_label = wili_test_y$V1

fasttext_isoc_name = isocodes_fasttext[, c(1,5)]
merg_labels_textc = merge(textc_dtbl, fasttext_isoc_name, by =
'Name_tolower')
# as.vector(colSums(is.na(merg_labels_cld2)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = merg_labels_textc$true_label,
               preds_data = merg_labels_textc$Alpha_3_B,
               method = 'textcat ( TC_char_profiles )')
```

```
## Total Rows: 50500
## Predicted Rows: 43265  (85.67% predicted)
## Missing Values:  7235
## Accuracy on 'Predicted Rows' using 'textcat ( TC_char_profiles )':  31.1%
```

```
## Elapsed time: 0 hours and 1 minutes and 39 seconds.
```

The **accuracy** of the **textcat** package using the **TC_char_profiles** is **31.10%** (on **43265** out of **50500** text extracts)

### Language recognition using the ‘franc’ R package

The R package port of Franc has no external dependencies and supports *310 languages*. All languages spoken by more than one million speakers. Franc is a port of the JavaScript project of the same name. Based on the documentation of the JavaScript project, *” … franc supports many languages, which means it’s easily confused on small samples. Make sure to pass it big documents to get reliable results …”*

The **franc()** function expects a text extract, therefore we will wrap the function with **parallel::mclapply()** as we've done with the *textcat* package to reduce the computation time. Moreover, we'll set the **min_speakers** parameter to **0** to include **all** languages known by franc (increasing the *max_length* parameter to *4096* does not improve the accuracy for this specific data / text extracts),

```
require(franc)

t_start = proc.time()
franc_res = as.vector(unlist(parallel::mclapply(1:length(wili_test_x$V1), function(x) {
  franc(text = wili_test_x$V1[x], min_speakers = 0, min_length = 10, max_length = 2048)
}, mc.cores = threads)))

franc_dtbl = data.table::setDT(list(franc = franc_res, true_label = wili_test_y$V1))
# as.vector(colSums(is.na(franc_dtbl)))

print_accuracy(size_input_data = nrow(wili_test_y),
               true_data = franc_dtbl$true_label,
               preds_data = franc_dtbl$franc,
               method = 'franc')
```

```
## Total Rows: 50500
## Predicted Rows: 50500  (100% predicted)
## Missing Values:  0
## Accuracy on 'Predicted Rows' using 'franc':  62.04%
```

```
## Elapsed time: 0 hours and 3 minutes and 6 seconds.
```

The **accuracy** of the **franc** package is **62.04%** (on **50500** out of **50500** text extracts)

## Overview datatable of all methods

Sorted by **Accuracy** (highest better),

```
##            method  rows pred_rows pred_perc   NAs accuracy seconds threads
## 1: fastText (bin) 50500     50168     99.34   332    86.55       5       1
## 2:           cld2 50500     34254     67.83 16246    83.13       2       1
## 3: fastText (ftz) 50500     50211     99.43   289    83.05       5       1
## 4:           cld3 50500     43560     86.26  6940    74.74      18       1
## 5:          franc 50500     50500    100.00     0    62.04     179       8
## 6: textcat (char) 50500     43265     85.67  7235    31.10     100       8
## 7: textcat (byte) 50500     47324     93.71  3176    29.91      83       8
```

Sorted by **predicted percentage of text extracts** (highest better),

```
##             method  rows pred_rows pred_perc   NAs accuracy seconds threads
## 1:           franc 50500     50500    100.00     0    62.04     179       8
## 2: fastText (ftz) 50500     50211     99.43   289    83.05       5       1
## 3: fastText (bin) 50500     50168     99.34   332    86.55       5       1
## 4: textcat (byte) 50500     47324     93.71  3176    29.91      83       8
## 5:            cld3 50500     43560     86.26  6940    74.74      18       1
## 6: textcat (char) 50500     43265     85.67  7235    31.10     100       8
## 7:            cld2 50500     34254     67.83 16246    83.13       2       1
```

Sorted by **missing values** (lowest better),

```
##             method  rows pred_rows pred_perc   NAs accuracy seconds threads
## 1:           franc 50500     50500    100.00     0    62.04     179       8
## 2: fastText (ftz) 50500     50211     99.43   289    83.05       5       1
## 3: fastText (bin) 50500     50168     99.34   332    86.55       5       1
## 4: textcat (byte) 50500     47324     93.71  3176    29.91      83       8
## 5:            cld3 50500     43560     86.26  6940    74.74      18       1
## 6: textcat (char) 50500     43265     85.67  7235    31.10     100       8
## 7:            cld2 50500     34254     67.83 16246    83.13       2       1
```

Sorted by **computation time** (lowest better),

```
##             method  rows pred_rows pred_perc   NAs accuracy seconds threads
## 1:            cld2 50500     34254     67.83 16246    83.13       2       1
## 2: fastText (ftz) 50500     50211     99.43   289    83.05       5       1
## 3: fastText (bin) 50500     50168     99.34   332    86.55       5       1
## 4:            cld3 50500     43560     86.26  6940    74.74      18       1
## 5: textcat (byte) 50500     47324     93.71  3176    29.91      83       8
## 6: textcat (char) 50500     43265     85.67  7235    31.10     100       8
## 7:           franc 50500     50500    100.00     0    62.04     179       8
```

## Benchmark based on the Human Rights Declaration files

We can test the mentioned functions also using the **Declaration of Human Rights** text files, which are smaller in size and can give hints on potential misclassifications. As I mentioned at the beginning of this blog post the data can be downloaded from two different internet sources. I'll use only 3 files from the *official website* based on the **total number of speakers worldwide** (the first 3 are: **Chinese**, **English**, **Spanish**) and you can see the full list of the most spoken languages worldwide in the correponding wikipedia article.

Assuming the **.zip** file is downloaded and extracted in the **dir_wili_2018** directory and the folder name that includes the files is named as **declaration_human_rights** then,

```
dir_files = file.path(dir_wili_2018, 'declaration_human_rights')
```

```
lst_files = list.files(dir_files, full.names = T, pattern = '.pdf')

decl_dat = lapply(1:length(lst_files), function(x) {

  iter_dat = pdftools::pdf_text(pdf = lst_files[x])
  lang = trimws(unlist(strsplit(gsub('.pdf', '',
basename(lst_files[x])), '_')), which = 'both')
  lang = lang[length(lang)]
  vec_txt = as.vector(unlist(trimws(iter_dat, which = 'both')))
  vec_txt = as.vector(sapply(vec_txt, function(x) gsub('\n', '', x)))

  idx_lang = which(isocodes_fasttext$Name_tolower == lang)
  isocode_3_language = rep(isocodes_fasttext$Alpha_3_B[idx_lang],
length(vec_txt))
  isocode_2_language = rep(isocodes_fasttext$Alpha_2[idx_lang],
length(vec_txt))
  language = rep(lang, length(vec_txt))

  dtbl = data.table::setDT(list(isocode_3_language =
isocode_3_language,
                                isocode_2_language =
isocode_2_language,
                                language = language,
                                text = vec_txt))
  dtbl
})

decl_dat = data.table::rbindlist(decl_dat)
```

```
decl_dat$language
```

```
##  [1] "chinese" "chinese" "chinese" "chinese" "chinese" "chinese" "chinese"
##  [8] "english" "english" "english" "english" "english" "english" "english"
## [15] "english" "spanish" "spanish" "spanish" "spanish" "spanish" "spanish"
## [22] "spanish" "spanish" "spanish"
```

```
decl_dat$isocode_3_language
```

```
##  [1] "chi" "chi" "chi" "chi" "chi" "chi" "chi" "eng" "eng" "eng" "eng" "eng"
## [13] "eng" "eng" "eng" "spa" "spa" "spa" "spa" "spa" "spa" "spa" "spa" "spa"
```

```
decl_dat$isocode_2_language
```

```
##  [1] "zh" "zh" "zh" "zh" "zh" "zh" "zh" "en" "en" "en" "en" "en" "en" "en" "en"
## [16] "es" "es" "es" "es" "es" "es" "es" "es" "es"
```

The output *data.table* includes besides the *language* also the language *isocodes* (consisting of 2 and 3 letters) and the *text extracts*. We can start to identify the language of these extracts using the **fastText** R package and utilizing the *small* pre-trained *'lid.176.ftz'* model,

```
dtbl_res_in = fastText::language_identification(input_obj =
decl_dat$text,

pre_trained_language_model_path = file_ftz,
                                                             k = 1,
                                                             th = 0.0,
                                                             threads = 1,
                                                             verbose = TRUE)
```

```
## The 'fasttext' algorithm starts ...
## The predicted labels will be loaded from the temporary file ...
## The temporary files will be removed ...
## Elapsed time: 0 hours and 0 minutes and 0 seconds.
```

```
dtbl_res_in
```

```
##     iso_lang_1   prob_1
##  1:         zh 0.983034
##  2:         zh 0.954020
##  3:         zh 0.972860
##  4:         zh 0.921718
##  5:         zh 0.956522
##  6:         zh 0.963453
##  7:         zh 0.977013
##  8:         en 0.965745
##  9:         en 0.949174
## 10:         en 0.971184
## 11:         en 0.976895
## 12:         en 0.961103
## 13:         en 0.972191
## 14:         en 0.952330
## 15:         en 0.955168
## 16:         es 0.967772
## 17:         es 0.976092
## 18:         es 0.963208
## 19:         es 0.972040
## 20:         es 0.970936
## 21:         es 0.976471
## 22:         es 0.977927
## 23:         es 0.972598
## 24:         es 0.978915
##     iso_lang_1   prob_1
```

To validate the results we will use the **isocode_2_language** column of the previous computed **decl_dat** data.table,

```
print_accuracy(size_input_data = length(dtbl_res_in$iso_lang_1),
               true_data = decl_dat$isocode_2_language,
               preds_data = dtbl_res_in$iso_lang_1,
               method = 'fastText (.ftz pre-trained model)')
```

```
## Total Rows: 24
## Predicted Rows: 24  (100% predicted)
## Missing Values:  0
## Accuracy on 'Predicted Rows' using 'fastText (.ftz pre-trained model)':  100%
```

There are no misclassifications for the 24 input text extracts using the *fastText* algorithm. We can move to the **cld2** R package and the corresponding language identification function,

```
cld2_vec = cld2::detect_language(text = decl_dat$text,
                                 plain_text = TRUE,
                                 lang_code = TRUE)
cld2_vec
```

```
##  [1] "zh" "zh" "zh" "zh" "zh" "zh" "zh" "en" "en" "en" "en" "en" "en" "en" "en"
## [16] "es" "es" "es" "es" "es" "es" "es" "es" "es"
```

```
print_accuracy(size_input_data = nrow(decl_dat),
               true_data = decl_dat$isocode_2_language,
               preds_data = cld2_vec,
               method = 'cld2')
```

```
## Total Rows: 24
## Predicted Rows: 24  (100% predicted)
## Missing Values:  0
## Accuracy on 'Predicted Rows' using 'cld2':  100%
```

There are no misclassifications for the **cld2** algorithm too. We'll test also **cld3**,

```
cld3_vec = cld3::detect_language(text = decl_dat$text)
cld3_vec
```

```
##  [1] "zh" "zh" "zh" "zh" "zh" "zh" "zh" "en" "en" "en" "en" "en" "en" "en" "en"
## [16] "es" "es" "es" "es" "es" "es" "es" "es" "es"
```

```
print_accuracy(size_input_data = nrow(decl_dat),
               true_data = decl_dat$isocode_2_language,
               preds_data = cld3_vec,
               method = 'cld3')
```

```
## Total Rows: 24
## Predicted Rows: 24  (100% predicted)
## Missing Values:  0
## Accuracy on 'Predicted Rows' using 'cld3':  100%
```

There are no misclassifications for the **cld3** algorithm, so we move to the **textcat** R package. The **'TC_byte_profiles'** include the **'chinese-gb2312'** language characters therefore we'll use these profiles in the **textcat** function,

```
textc = textcat(x = decl_dat$text, p = textcat::TC_byte_profiles,
method = "CT")
textc
```

```
##  [1] "japanese-shift_jis" "japanese-shift_jis" "japanese-shift_jis"
##  [4] "japanese-shift_jis" "japanese-shift_jis" "japanese-shift_jis"
##  [7] "japanese-shift_jis" "english"            "english"
## [10] "english"            "english"            "english"
## [13] "english"            "english"            "english"
## [16] "spanish"            "spanish"            "spanish"
## [19] "spanish"            "spanish"            "spanish"
## [22] "spanish"            "spanish"            "spanish"
```

```
textc = as.vector(unlist(lapply(strsplit(textc, '-'), function(x)
x[1])))
textc = trimws(textc, which = 'both')
textc
```

```
##  [1] "japanese" "japanese" "japanese" "japanese" "japanese" "japanese"
##  [7] "japanese" "english"  "english"  "english"  "english"  "english"
## [13] "english"  "english"  "english"  "spanish"  "spanish"  "spanish"
## [19] "spanish"  "spanish"  "spanish"  "spanish"  "spanish"  "spanish"
```

```
print_accuracy(size_input_data = nrow(decl_dat),
               true_data = decl_dat$language,
               preds_data = textc,
               method = 'textcat')
```

```
## Total Rows: 24
## Predicted Rows: 24  (100% predicted)
## Missing Values:  0
## Accuracy on 'Predicted Rows' using 'textcat':  70.83%
```

The **textcat** package misclassifies the *chinese text extracts* as *'japanese-shift_jis'*, therefore the accuracy *drops to approx. 70%*. Finally, we'll test the **franc** package,

```
franc_vec = as.vector(sapply(decl_dat$text, function(x) {
  franc(text = x, min_length = 10, max_length = 2048)
}))
```

```
franc_vec
```

```
##  [1] "cmn" "cmn" "cmn" "cmn" "cmn" "cmn" "cmn" "eng" "eng" "eng" "eng" "eng"
## [13] "eng" "eng" "eng" "spa" "spa" "spa" "spa" "spa" "spa" "spa" "spa" "spa"
```

```
print_accuracy(size_input_data = nrow(decl_dat),
               true_data = decl_dat$isocode_3_language,
               preds_data = franc_vec,
               method = 'franc')
```

```
## Total Rows: 24
## Predicted Rows: 24  (100% predicted)
## Missing Values:  0
## Accuracy on 'Predicted Rows' using 'franc':  70.83%
```

The **franc** function identified the *chinese* text excerpts as *mandarin* chinese, therefore I personally would not consider these as misclassifications (as *mandarin* is a dialect of the chinese language). We can have an overview of the results of the different methods by illustrating the outputs in a single data.table,

```
dtbl_out = decl_dat[, 1:3]
colnames(dtbl_out) = c('true_y_iso_3', 'true_y_iso_2',
'true_y_language')
# dtbl_out

dtbl_preds = data.table::setDT(list(fastText = dtbl_res_in$iso_lang_1,
                                    cld2 = cld2_vec,
                                    cld3 = cld3_vec,
                                    textcat = textc,
                                    franc = franc_vec))
# dtbl_preds

dtbl_out = cbind(dtbl_out, dtbl_preds)
dtbl_out
```

```
##     true_y_iso_3 true_y_iso_2 true_y_language fastText cld2 cld3  textcat franc
##  1:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  2:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  3:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  4:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  5:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  6:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  7:          chi           zh         chinese       zh   zh   zh japanese   cmn
##  8:          eng           en         english       en   en   en  english   eng
##  9:          eng           en         english       en   en   en  english   eng
## 10:          eng           en         english       en   en   en  english   eng
## 11:          eng           en         english       en   en   en  english   eng
## 12:          eng           en         english       en   en   en  english   eng
## 13:          eng           en         english       en   en   en  english   eng
## 14:          eng           en         english       en   en   en  english   eng
## 15:          eng           en         english       en   en   en  english   eng
## 16:          spa           es         spanish       es   es   es  spanish   spa
## 17:          spa           es         spanish       es   es   es  spanish   spa
## 18:          spa           es         spanish       es   es   es  spanish   spa
## 19:          spa           es         spanish       es   es   es  spanish   spa
## 20:          spa           es         spanish       es   es   es  spanish   spa
## 21:          spa           es         spanish       es   es   es  spanish   spa
## 22:          spa           es         spanish       es   es   es  spanish   spa
## 23:          spa           es         spanish       es   es   es  spanish   spa
## 24:          spa           es         spanish       es   es   es  spanish   spa
##     true_y_iso_3 true_y_iso_2 true_y_language fastText cld2 cld3  textcat franc
```

## Comparison between ‘fastText’, ‘cl2’, ‘cl3’ and ‘franc’ for Multilingual output

Finally, we can observe the output of **fastText**, **cl2**, **cl3** and **franc** for Multilingual output (I’ll exclude the **textcat::textcat()** function, because it expects a single language per character string in the input vector).

- We will first tokenize all three **Declaration of Human Rights** text files, then
- we will sample a specific number of words of the tokenized output and
- build a sentence that will be classified using the mentioned algorithms.

In order to verify the results and see how each algorithm performs we will pick **100 words** of each declaration file. Due to the fact that the **chinese** language has **ambiguous word boundaries** we will use the **stringi::stri_split_boundaries()** function of the **stringi** R package to extract the words of the chinese text file. The following function shows the pre-processing steps to come to the multilingual sentence,

```
lst_files = list.files(dir_files, full.names = F, pattern = '.pdf')

min_letters_en_es = 3          # min. number of characters for the 'en'
and 'es' languages
sample_words = 100             # sample that many words from each
tokenized file

decl_dat = lapply(1:length(lst_files), function(x) {
```

```
  iter_dat = pdftools::pdf_text(pdf = file.path(dir_files,
lst_files[x]))

  dat_txt = sapply(iter_dat, function(y) {

    if (lst_files[x] == 'declaration_human_rights_chinese.pdf') {
      res_spl_lang = stringi::stri_split_boundaries(str = y,
                                                     type = 'word',
                                                     skip_word_none =
TRUE,
                                                     skip_word_letter =
TRUE,
                                                     skip_word_number =
TRUE)
    }
    else {
      res_spl_lang = stringi::stri_split(str = y,
                                        regex = '[ \n,]',
                                        omit_empty = TRUE,
                                        tokens_only = TRUE)
    }

    res_spl_lang = trimws(res_spl_lang[[1]], which = 'both')
    idx_empty = which(res_spl_lang == "")
    if (length(idx_empty) > 0) {
      res_spl_lang = res_spl_lang[-idx_empty]
    }
    if (!is.null(min_letters_en_es) & lst_files[x] !=
'declaration_human_rights_chinese.pdf') {
      nchars = nchar(res_spl_lang)
      idx_chars = which(nchars >= min_letters_en_es)
      if (length(idx_chars) > 0) {
        res_spl_lang = res_spl_lang[idx_chars]
      }
    }
    res_spl_lang
  })

  dat_txt = as.vector(unlist(dat_txt))
  set.seed(1)
  sample_words = sample(dat_txt, sample_words)
  sample_words
})


decl_dat = as.vector(unlist(decl_dat))
decl_dat = decl_dat[sample(1:length(decl_dat), length(decl_dat))]
multilingual_sentence = paste(decl_dat, collapse = ' ')
multilingual_sentence
```

```
## [1] "the 的 iguales condenado morales podrá elecciones committed. the 利 合 经 voting 加
tribunal basis 种 caso 利 property 奴 intereses 界 protection. Todos 害 是 联 público 上 equal
directly artistic Toda cada States Nadie barbarous was 条 universal una pensamiento
reputación. tiene beyond pérdida debe due 这 materiales Nations fundamental 十八条 habida
protection United Everyone 基本 受 fin persona rebellion derecho 校 Article circunstancias
cualquier this for 所 todas personalidad alguna los 文 定 持 罪 causa públicamente nacionalidad
需 spirit with country. dignidad should and Estado. 术 have without 由 人 los 公 tiene 的 正
acts law 给予 act 而 todos internacional. mujeres; 行 and proclamados 的 自 las this 自
personalidad. 庭 的 trial idioma was 住 fiduciaria elegir 一 respecto 和 有 Toda cualquier 本 受
defence. por derecho opinión 婚 任 territorio derecho 期 one del hours origin étnicos 权
Considerando any instrucción ley 一 任 seek 或 人 the las domicilio 任 igual part through 遍 one
international constitute tienen 得 均 indispensables 适 autónomo 或 los and 视 有 free 教
recibir así right 或 地 personalidad among libres podrán orden elemental 援 menosprecio Article
persona 尊 freedoms raza objeto world has remedy amistad development Artículo service acts 攻
equal 和 democratic the 以 treatment descanso humano Artículo otra 民 和 由 Education means 渐
actos 为 law Nations. 些 良 merit. the asistencia childhood law has por equal 颁 定 展 The
dignity others control. 由 的 maintenance 会 和 group one 并 内 régimen share opuestos
jurisdictional 有 人 善 right the las and derechos 和 保 genuine Los 的 set actos 人 puesto ley
shall 成 right torture propiedad derecho 公 voluntad. otra special for 保 has 现 的 buscar ideas
透 合 discrimination 资 tiene desconocimiento"
```

We deliberately mixed the words by first sampling the vector and then concatenating the tokens to a sentence. The purpose of the multilingual identification is to find out if each algorithm detects the *correct languages* assuming the *number of languages* in the text are *known beforehand*.

Imagine, you have 3 people having a conversation in a room where interchangeably a different language is spoken and this conversation is recorded by a fourth person.

```
num_languages = 3
```

**fastText Multilingual**

```
dtbl_multiling = fastText::language_identification(input_obj = multilingual_sentence,

pre_trained_language_model_path = file_ftz,
                                                   k = num_languages,
                                                   th = 0.0,
                                                   threads = 1,
                                                   verbose = FALSE)
dtbl_multiling
```

```
##    iso_lang_1   prob_1 iso_lang_2   prob_2 iso_lang_3    prob_3
## 1:         es 0.399272         ja 0.359435         zh 0.0897425
```

### cld2 Multilingual

```
cld2::detect_language_mixed(text = multilingual_sentence, plain_text =
TRUE)$classification
```

```
##   language code latin proportion
## 1  ENGLISH   en  TRUE       0.37
## 2  SPANISH   es  TRUE       0.34
## 3  CHINESE   zh FALSE       0.08
```

### cld3 Multilingual

```
cld3::detect_language_mixed(text = multilingual_sentence, size =
num_languages)
```

```
##   language probability reliable proportion
## 1       es   0.9120256     TRUE  0.3501965
## 2       zh   0.9908968     TRUE  0.2259332
## 3       en   0.7694073     TRUE  0.1517682
```

### franc Multilingual

```
# we could use the 'whitelist' parameter but the purpose is to identify
languages from unknown text

franc::franc_all(text = multilingual_sentence, max_length =
nchar(multilingual_sentence) + 1)[1:num_languages, ]
```

```
##   language     score
## 1      spa 1.0000000
## 2      eng 0.9985168
## 3      glg 0.9813168
```

From the results one can come to the following **conclusions**:

- the **cld2** *detect_language_mixed()* function detects the correct languages without even specifying how many languages are in the text

- the **cld3** *detect_language_mixed()* function detects the correct languages (as *cld2*) but with the *limitation* that we have to specify the number of languages beforehand
- the **fastText** function, detects 2 out of the 3 languages and the false detected one (*japanese*) seems to receive a higher probability than *chinese* (*english* is not detected at all)
- the **franc** *franc_all()* function detects correctly 2 out of the 3 languages (*english* and *spanish*) but not chinese (the third language based on score is *Galician*)