oolong: An R package for validating automated content analysis tools

Chung-hong Chan[1] **and Marius Sältzer**[1]

1 Mannheimer Zentrum für Europäische Sozialforschung, Universität Mannheim

Statement of need

Oolong is an R package providing functions for semantic validation of topic modeling and dictionary-based methods, two main tools for doing automated content analysis (Boumans & Trilling, 2016; Günther & Quandt, 2016).

While the validation of statistical properties of topics models is well established, the substantive meaning of categories uncovered is often less clear and their interpretation reliant on "intuition" or "eyeballing". As Chang, Gerrish, Wang, Boyd-Graber, & Blei (2009, p. 1) put it: "qualitative evaluation of the latent space" or figuratively, reading tea leaves.

The story for dictionary-based methods is not better. Researchers usually assume these dictionaries have built-in validity and use them directly in their research. However, multiple validation studies (Boukes, Velde, Araujo, & Vliegenthart, 2020; González-Bailón & Paltoglou, 2015; Ribeiro, Araújo, Gonçalves, Gonçalves, & Benevenuto, 2016) demonstrate these dictionaries have very limited criterion validity.

Oolong provides a set of tools to objectively judge substantive interpretability to applied users in disciplines such as political science and communication science. It allows standardized content based testing of topic models as well as dictionary-based methods with clear numeric indicators of semantic validity. Oolong makes it easy to generate standard validation tests suggested by Chang et al. (2009) and Song et al. (2020).

Validation of automated content analysis

Validity is a requirement of content analysis (Krippendorff, 2018; Neuendorf, 2016). Validation of automated methods has been called for by many scholars, e.g. Grimmer & Stewart (2013); Ribeiro et al. (2016); Van Atteveldt & Peng (2018). But how to validate these methods? The paper by DiMaggio, Nag, & Blei (2013) conceptualizes validation of automated methods as three different operations and the three operations supplement each other. These three operations are: 1) *statistical* validation –to see if the model results agree with the assumptions of the model. Examples of statistical validation are calculation of pointwise mutual information, perplexity or semantic coherence of a topic model; 2) *semantic* validation –to see if the model results are semantically making sense. This procedure involves comparing model results with human judgment (Grimmer & King, 2011); 3) *predictive* validation –to see if the model results can predict external events (Quinn, Monroe, Colaresi, Crespin, & Radev, 2010). For example, one can study whether external events can explain surges in attention to a topic extracted by a topic model.

This package focuses on semantic validation for three reasons: First, there is existing architecture for conducting statistical validation and predictive validation. Topic modeling packages such as `text2vec` (Selivanov, Bickel, & Wang, 2020), `topicmodels` (Grün & Hornik, 2011), and `textmineR` (Jones, 2019) provide functions to calculate metrics such as perplexity and semantic coherence. Packages such as `stminsights` (Schwemmer, 2018) and `LDAvis` (Sievert & Shirley, 2015) offer additional qualitative methods for predictive validation. As of writing, `tosca` (Koppers, Rieger, Boczek, & von Nordheim, 2020) is the only package dealing with semantic validation. But the text-based interface might pose challenges to human annotators and it can only support topic models from the `lda` package (Chang, 2015).

Second, results from statistical validation do not always agree with those from semantic validation. For example, a topic model with a lower perplexity does not have a better interpretability (Chang et al., 2009). Of course, there are also metrics from statistical validation that are shown to be correlated with semantic validity, e.g. semantic coherence (Mimno, Wallach, Talley, Leenders, & McCallum, 2011). But this correlation is also dependent on the text material. For example, Fan, Doshi-Velez, & Miratrix (2019) show that semantic coherence is weakly correlated at best with human assessment, when the text material used for training a topic model has some frequent terms. But still, calculation of semantic coherence is recommended in the best practice paper by Maier et al. (2018). Nonetheless, conducting only statistical validation is not adequate because these three validation operations supplement each other.

Finally, predictive validation is dependent on research questions and thus it is difficult to be generalized as a reusable software framework. Additionally, the relationship between external (sociopolitical) events and the results from automated content analysis tools is usually what social scientists are eager to study, cf. using topic models for information retrieval (Yi & Allan, 2008). We do not believe social scientists would ignore conducting any form of predictive validation.

Oolong focuses on semantic validation. The package provides the "human-in-the-loop" semantic validation procedures suggested by Chang et al. (2009) and Song et al. (2020). The procedure proposed by Chang et al. (2009) has been adopted in subsequent social science studies as the gold standard to validate topic models, e.g. Bohr (2020), Chuang et al. (2015), and Miller (2017). The procedure proposed by Song et al. (2020) emphasizes both criterion validity and interrater reliability.

Semantic validation of topic models

Topic models can be validated by word intrusion test and topic intrusion test (Chang et al., 2009). In these tests, a human rater is asked to pick an odd word from a bunch of words (word intrusion test) or pick an odd topic from a bunch of topics for a document (topic intrusion test). Oolong provides an easy-to-use Shiny interface for these tests (Figure 1).

Currently, oolong supports a variety of topic models, e.g. structural topic models / correlated topic models from `stm` (Roberts, Stewart, & Tingley, 2019), warp-LDA models from `text2vec` (Selivanov et al., 2020), latent dirichlet allocation / correlated-topic models from `topicmodels` (Grün & Hornik, 2011), biterm topic models from `BTM` (Wijffels, 2020) and keyword-assisted topic models from `keyATM` (Eshima, Imai, & Sasaki, 2020).

For instance, `abstracts_stm` is a structural topic model trained with the text data from `abstracts$text` (Chan & Grill, 2020).

```
library(stm)
library(tibble)
library(dplyr)
```

Figure 1: A screenshot of word intrusion test

```
library(quanteda)
library(oolong)
```

```
abstracts_stm
```

```
## A topic model with 20 topics, 2500 documents and a 3998 word dictionary.
```

```
abstracts
```

```
## # A tibble: 2,500 x 1
##    text
##    <chr>
##  1 This study explores the benefits and risks featured in medical tourism broke
##  2 This article puts forth the argument that with the transfer of stock trading
##  3 The purpose of this study was to evaluate the effect the visual fidelity of
##  4 Among the many health issues relevant to college students, overconsumption o
##  5 This address, delivered at ICA's 50th anniversary conference, calls on the a
##  6 The Internet has often been used to reach men who have sex with men (MSMs) i
##  7 This article argues that the literature describing the internet revolution i
##  8 This research study examined Bud Goodall's online health narrative as a case
##  9 Information technology and new media allow for collecting and sharing person
## 10 Using a national, telephone survey of 1,762 adolescents aged 12-17 years, th
## # ... with 2,490 more rows
```

The function `create_oolong` creates a test object with both word intrusion test and topic intrusion test.

```
oolong_test <- create_oolong(input_model = abstracts_stm,
                             input_corpus = abstracts$text)
oolong_test
```

```
## An oolong test object with k = 20, 0 coded.
```

```
## Use the method $do_word_intrusion_test() to do word intrusion test.
## With 25 cases of topic intrusion test. 0 coded.
## Use the method $do_topic_intrusion_test() to do topic intrusion test.
## Use the method $lock() to finalize this object and see the results.
```

The tests can be administered with methods `do_word_intrusion_test` and `do_topic_intrusion_test`.

```
oolong_test$do_word_intrusion_test()
oolong_test$do_topic_intrusion_test()
```

After both tests has been done by a human rater, the test object must be locked and then accuracy metrics such as model precision (MP) and TLO (topic log odd) are displayed.

```
oolong_test$lock()
oolong_test
```

```
## An oolong test object with k = 20, 20 coded.
## 95%  precision
## With 25 cases of topic intrusion test. 25 coded.
## TLO: -0.121
```

The suggested workflow is to have at least two human raters to do the same set of tests. Test object can be cloned to allow multiple raters to do the test. More than one test object can be studied together using the function `summarize_oolong()`.

```
oolong_test_rater1 <- create_oolong(abstracts_stm, abstracts$text)
oolong_test_rater2 <- clone_oolong(oolong_test_rater1)
```

```
## Let rater 1 do the test.
oolong_test_rater1$do_word_intrusion_test()
oolong_test_rater1$do_topic_intrusion_test()
oolong_test_rater1$lock()

## Let rater 2 do the test.
oolong_test_rater2$do_word_intrusion_test()
oolong_test_rater2$do_topic_intrusion_test()
oolong_test_rater2$lock()
```

Get a summary of the two objects.

```
summarize_oolong(oolong_test_rater1, oolong_test_rater2)
```

```
## New names:
## * NA -> ...1
## * NA -> ...2

## Mean model precision: 0.325
## Quantiles of model precision: 0.25, 0.2875, 0.325, 0.3625, 0.4
## P-value of the model precision (H0: Model precision is not better than random g
## Krippendorff's alpha: 0.444444444444444
## K Precision: 0, 0, 1, 0.5, 0, 1, 0, 0.5, 0.5, 0, 0, 0, 0, 1, 0, 0, 1, 0.5, 0, 0
## Mean TLO: -2.54
## Median TLO: -2.72
## Quantiles of TLO: -6.33889942140902, -4.26355037534241, -2.7177571693671, 0, 0
## P-Value of the median TLO (H0: Median TLO is not better than random guess): 0.5
```

Semantic validation of dictionary-based methods

Dictionary-based methods such as AFINN (Nielsen, 2011) can be validated by creating a gold standard dataset (Song et al., 2020). Oolong provides a workflow for generating such gold standard dataset.

For example, you are interested in studying the sentiment of tweets from Donald Trump. `trump2k` is a random subset of 2,000 tweets from Donald Trump. And you would like to use AFINN to extract sentiment from these tweets. In this analysis, AFINN sentiment score is the *target value*.

```
tibble(text = trump2k)
```

```
## # A tibble: 2,000 x 1
##    text
##    <chr>
##  1 "In just out book, Secret Service Agent Gary Byrne doesn't believe that Croo
##  2 "Hillary Clinton has announced that she is letting her husband out to campai
##  3 "\"@TheBrodyFile: Always great to visit with @TheBrodyFile one-on-one with \
##  4 "Explain to @brithume and @megynkelly, who know nothing, that I will beat Hi
##  5 "Nobody beats me on National Security. https://t.co/sCrj4Ha1I5"
##  6 "\"@realbill2016: @realDonaldTrump @Brainykid2010 @shl Trump leading LA Time
##  7 "\"@teapartynews: Trump Wins Tea Party Group's 'Nashville Straw Poll' - News
##  8 "Big Republican Dinner tonight at Mar-a-Lago in Palm Beach. I will be there!
##  9 ".@HillaryClinton loves to lie. America has had enough of the CLINTON'S! It
## 10 "\"@brianstoya: @realDonaldTrump For POTUS #2016\""
## # ... with 1,990 more rows
```

A test object can be generated also with `create_oolong`. The argument `construct` should be an adjective, e.g. "positive" or "liberal".

```
trump <- create_oolong(input_corpus = trump2k,
                       construct = "positive",
                       exact_n = 20)
trump
```

```
## An oolong test object (gold standard generation) with 20 cases, 0 coded.
## Use the method $do_gold_standard_test() to generate gold standard.
## Use the method $lock() to finalize this object and see the results.
```

Similarly, we suggest to have at least two human coders to do the same set of tests.

```
trump2 <- clone_oolong(trump)
```

Instruct two coders to code the tweets and lock the objects.

```
trump$do_gold_standard_test()
trump2$do_gold_standard_test()
trump$lock()
trump2$lock()
```

The method `turn_gold` converts a test object into a quanteda corpus (Benoit et al., 2018).

```
gold_standard <- trump$turn_gold()
gold_standard
```

```
## Corpus consisting of 20 documents and 1 docvar.
## text1 :
## "Thank you Eau Claire, Wisconsin.  #VoteTrump on Tuesday, Apr..."
##
## text2 :
## ""@bobby990r_1: @realDonaldTrump would lead polls the second ..."
##
## text3 :
## ""@KdanielsK: @misstcassidy @AllAboutTheTea_ @realDonaldTrump..."
##
## text4 :
## "Thank you for a great afternoon Birmingham, Alabama! #Trump2..."
##
## text5 :
## ""@THETAINTEDT: @foxandfriends @realDonaldTrump Trump 2016 ht..."
##
## text6 :
## "People believe CNN these days almost as little as they belie..."
##
## [ reached max_ndoc ... 14 more documents ]
## Access the answer from the coding with quanteda::docvars(obj, 'answer')
```

This corpus can be used to calculate the target value, e.g. AFINN.

```
dfm(gold_standard, remove_punct = TRUE) %>% dfm_lookup(afinn) %>%
    quanteda::convert(to = "data.frame") %>%
    mutate(matching_word_valence = (neg5 * -5) + (neg4 * -4) +
            (neg3 * -3) + (neg2 * -2) + (neg1 * -1) +
            (zero * 0) + (pos1 * 1) + (pos2 * 2) + (pos3 * 3) +
            (pos4 * 4) + (pos5 * 5),
        base = ntoken(gold_standard, remove_punct = TRUE),
        afinn_score = matching_word_valence / base) %>%
        pull(afinn_score) -> afinn_score
```

Summarize all oolong objects with the target value.

```
res <- summarize_oolong(trump, trump2, target_value = afinn_score)
```

Printing the summary shows Krippendorff's Alpha, an indicator of interrater reliability. The validity metrics of a text analytic method can be tinted by poor interrater reliability of manual annotations (Song et al., 2020). It is important to ensure high interrater reliability first.

```
res
```

```
## Krippendorff's Alpha: 0.931443661971831
## Correlation: 0.744 (p = 0)
## Effect of content length: -0.323 (p = 0.164)
```
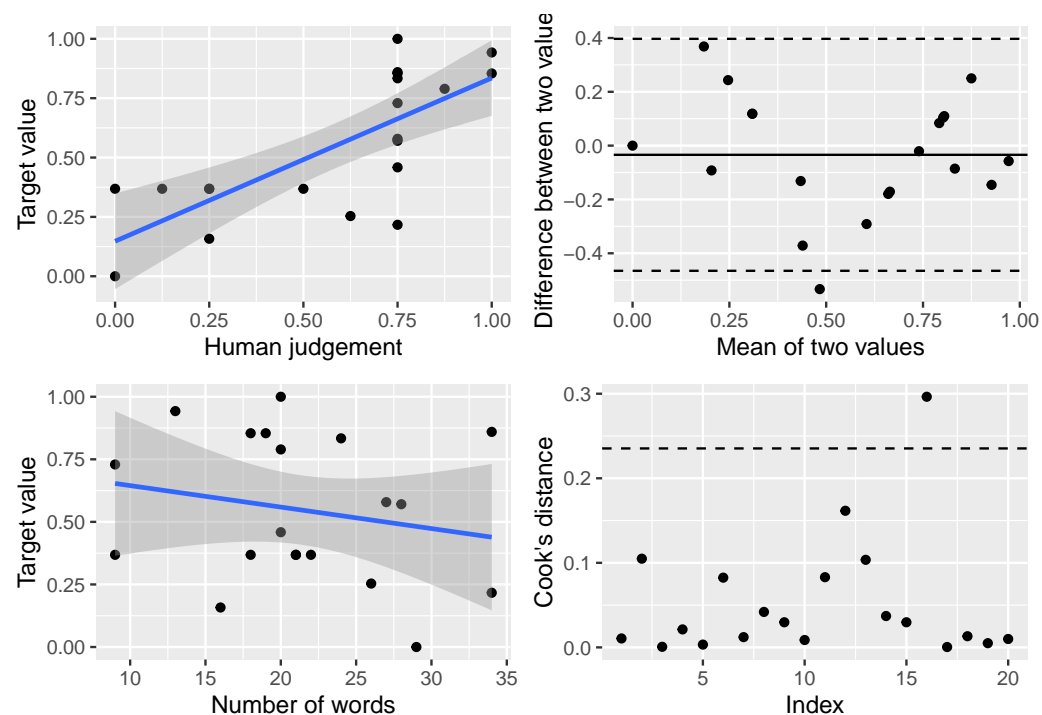
Figure 2: Diagnostic plots generated by oolong

Additional diagnostic plots can also be displayed.

```
plot(res)
```

The 4 subplots from left to right, top to bottom are: 1) correlation between human judgement and target value; 2) Bland-Altman plot; 3) correlation between target value and content length and 4) Cook's distance of all data point. These plots are helpful to determine criterion validity, agreement, robustness against content length and outliers of the target value.

Acknowledgements

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