CONTENT ANALYSIS DICTIONARIES 2

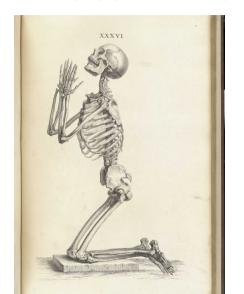
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SOLUTIONS: SOME THEOLOGICAL APPROACHES

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How bad is it?

- → Recall: the proportion of words used that way that are in your dictionary
- → Precision: the proportion of words used the way your dictionary assumes they are used

Precision and recall

Every field reinvents this distinction:

- → precision and recall
- → specificity and sensitivity
- → users and producer's accuracy
- → type 1 and type 2 error
- → sins of omission and sins of commission

PRECISION

Keyword in context analyses (KWIC) allow you to scan all contexts of a word

→ How many of them *are* the sense or usage you want?

Let's take a look at benefit* as a 'pro government intervention in the economy' word

| | pre | keyword | post |
|----|--|-----------|--|
| 1 | also keep all the other | benefits | that pensioners currently receive, |
| 2 | regulation will have to have | benefits | exceeding costs, and regulations |
| 3 | and Controlled Immigration Britain has | benefited | from immigration . We all |
| 4 | positive contribution But if those | benefits | are to continue to flow |
| 5 | Northern Ireland brings | benefits | to all parts of our |
| 6 | their home, will also | benefit | first-time buyers . Empowering individuals |
| 7 | you help yourself; you | benefit | and the country benefits . |
| 8 | you benefit and the country | benefits | . So now , I |
| 9 | result of our tax and | benefit | measures compared to 1997. |
| 10 | result of personal tax and | benefit | measures introduced since 1997, |
| 11 | , the savings on unemployment | benefits | will go towards investing more |
| 12 | trebled the number on incapacity | benefits | . We will help 17 |
| 13 | Work programme and reform Incapacity | Benefit | , with the main elements |
| 14 | main elements of the new | benefit | regime in place from 2008 |
| 15 | stronger penalties . To the | benefit | of business and household consumers |
| 16 | effective directive to provide real | benefits | to consumers and new opportunities |
| 17 | better.We are examining the potential | benefits | of a parallel Expressway on |
| 18 | ways to lock in the | benefit | of new capacity . We |
| 19 | are determined to spread the | benefits | of enterprise to every community |
| 20 | to get ahead , to | benefit | from improving public services |

PRECISION

Of the 20 instances, these are (arguably)

- → 6 used the way we expect from the topic
- → 3 used in the opposite sense: anti-government intervention in the economy
- → 11 used in ways that are neither

So...0.3 correct, 0.15 mistaken, and 0.55 unrelated 'noise'

→ Perhaps not an amazing choice

There are two kinds of precision failures here with different consequences

- → Mistaking an *topic-unrelated* word for this topic (11 of these)
- → Mistaking a word used in the sense of a *different* topic for this one (3 of these)

The first mistake does not really harm precision, but the second does

RECALL

Bad recall is a mixture of two problems

- → Assigning words to a topic that are mostly used for a different one: $P(W \mid Z = k) < P(W \mid Z = j)$ but we assigned it to k anyway
- \rightarrow Failing to assign a topic-informative word to any topic: Dictionary says $P(W \mid Z = k) = 0$, but it's not. This is about *coverage*

Let's consider coverage first

COVERAGE

One possible checking procedure:

- → Take a random matched sample of words not in the dictionary but present in the corpus e.g. match each dictionary word to another of the same frequency
- → Examine their KWICs to see if they should have been assigned to a topic

If we were feeling even more energetic

- → Assign them their most likely topic manually
- ightarrow Compare this $\tilde{\theta}$ to the dictionary's own estimate θ
- → These should not be wildly different

RECALL

The other kind of mistake is difficult because the natural procedure is

- → Assign *every word* (or at least every instance of a word that the dictionary knows about in a document) to a topic
- → For each topic, see what proportion of times the dictionary agrees it is in that topic

This also promises to be very tiring.

)

However, two facts may help us:

- → We have a tireless computer available
- \rightarrow Recall and precision relate $P(W \mid Z)$ and $P(Z \mid W)$ respectively
- → ...and we know how

Let's call the *true* topic of a word Z as before, and the *dictionary's idea of the topic* of a word Z because it's kind of an estimate of that. So,

Recall:
$$\sum_{k}^{K} P(\hat{Z} = k \mid Z = k)$$

Precision:
$$\sum_{k}^{K} P(Z = k \mid \hat{Z} = k)$$

If we have a sense of dictionary topic precision, could we use it to get a sense of dictionary topic recall?

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According to the Rev. Bayes

$$P(\hat{Z} = k \mid Z = k) = \frac{P(Z = k \mid \hat{Z} = k)P(\hat{Z} = k)}{\sum_{j}^{K} P(Z = j \mid \hat{Z} = j)P(\hat{Z} = j)}$$

$$= P(Z = k \mid \hat{Z} = k)\frac{P(\hat{Z} = k)}{P(Z = k)}$$
 (recall is reweighted precision)
$$\propto P(Z = k \mid \hat{Z} = k)P(\hat{Z} = k)$$

Conveniently

- → we don't need the denominator because it only ensure the recall measures add to one
- \rightarrow We can get $P(\hat{Z} = k)$ by running the dictionary over the entire corpus

PERSPECTIVE

Precision and recall are useful, but we are most interested in the *consequences* of being wrong Previously: consequences for a left-right ideology measure from Laver and Garry (2000)

Let's look at a related conflict-cooperation score assigned by experts to dictionary 'topics' (King & Lowe, 2003)

A machine coding system 'read' Agence France Press leads on the Bosnian wars and generated event data

→ Who did what to whom when

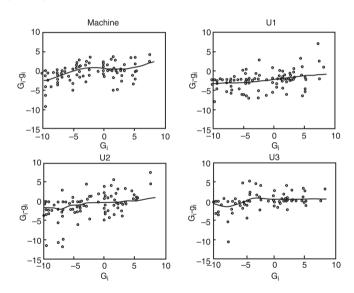
We were interested in evaluating the 'what'

- → Topics are event types in a large ontology of international events
- → topic *scores* represent how conflictual or cooperative that event is
- → Some topic categorization mistakes will matter more than others

EVENT TOPICS

| Goldstein | IDEA | Definition | Goldstein | IDEA | Definition |
|-----------|------|--------------------------------|-----------|------|-------------------------------|
| 0.1 | 091 | ask for information | -7.6 | 1826 | military border fortification |
| 0.1 | 024 | optimistic comment | -7.6 | 1825 | military mobilization |
| 0 | 99 | sports contest | -7.6 | 1824 | military troops display |
| 0 | 98 | A and E performance | -7.6 | 1823 | military naval display |
| 0 | 97 | accident | -7.6 | 1821 | military alert |
| 0 | 96 | natural disaster | -7.6 | 182 | military demonstration |
| 0 | 95 | human death | -8.3 | 224 | riot or political turmoil |
| 0 | 94 | human illness | -8.7 | 221 | bombings |
| 0 | 72 | animal death | -9.2 | 2236 | military seizure |
| 0 | 27 | economic status | -9.2 | 2123 | abduction |
| 0 | 26 | adjust | -9.2 | 211 | seize possession |
| 0 | 25 | vote | -9.6 | 2228 | assassination |
| 0 | 24 | adjudicate | -9.6 | 2227 | guerrilla assault |
| 0 | 2321 | government default on payments | -9.6 | 2226 | paramilitary assault |
| 0 | 2312 | private transactions | -9.6 | 2225 | torture |
| 0 | 2311 | government transactions | -9.6 | 2224 | sexual assault |
| 0 | 231 | transactions | -9.6 | 2223 | bodily punishment |
| 0 | 23 | economic activity | -9.6 | 2222 | shooting |
| -0.1 | 094 | ask for protection | -9.6 | 2221 | beatings |
| -0.1 | 022 | pessimistic comment | -9.6 | 222 | physical assault |
| -0.1 | 021 | decline comment | -9.6 | 22 | force |
| -0.1 | 02 | comment | -10 | 2237 | biological weapons use |
| -0.9 | 141 | deny responsibility | -10 | 2235 | assault |
| -1 | 14 | deny | -10 | 2234 | military occupation |
| -1.1 | 0631 | grant asylum | -10 | 2233 | coups and mutinies |
| -2.2 | 192 | reduce routine activity | -10 | 2232 | military raid |
| -2.2 | 121 | criticize or blame | -10 | 223 | military engagements |
| -2.4 | 132 | formally complain | | | , , , |
| 0.4 | 101 | | | | |

TOPIC SCORES



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Not bad (or at least not bad relative to undergraduate coders)

All the evaluation principles we've seen here apply to

- → document classifiers
- → content analysis dictionaries
- → human coders

Nothing is more practical than a good theory...

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Next week we'll see how we learn dictionaries rather than write them

→ but all the same considerations will apply

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- King, G. & Lowe, W. (2003). 'An automated information extraction tool for international conflict data with performance as good as human coders: A rare events evaluation design'. *International Organization*, 57(3), 617–642.
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