PHILOSOPHICAL WRITING IN EARLY NEW ZEALAND NEWSPAPERS

Joshua Black

February 5, 2021

UC ARTS
DIGITAL LAB

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   - a method applicable for many humanities research questions,
   - but with shortcomings to be aware of.

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- An example of the kind of thing we're after:

The following is a brief abstract of the Debate held at the Town Hall East Oxford, on Thursday, 9th.

(Continued from last week.)

6. A simple form of metaphysical argument may be briefly put as follows:—All existence are of two kinds necessary and contingent. By a necessary existence is meant one which never began to be, and can never cease to be. By a contingent existence is meant one which commenced to be and will cease to be. My exist-

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  - We will engage in ‘distant reading’ (Moretti 2013)

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   - This presentation will focus on co-occurrence networks.

METHOD

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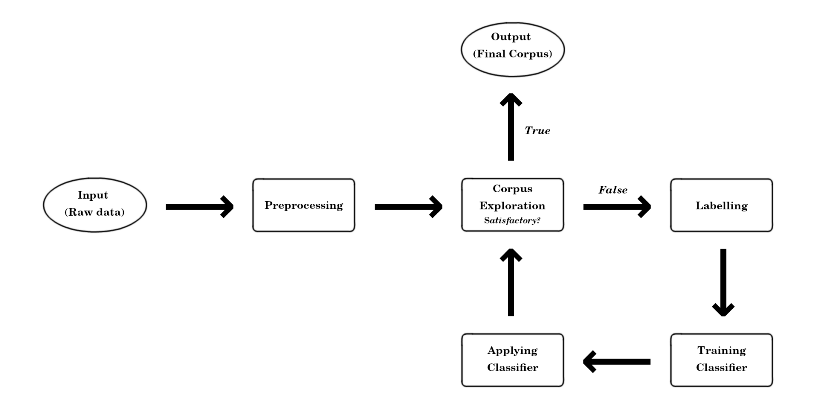

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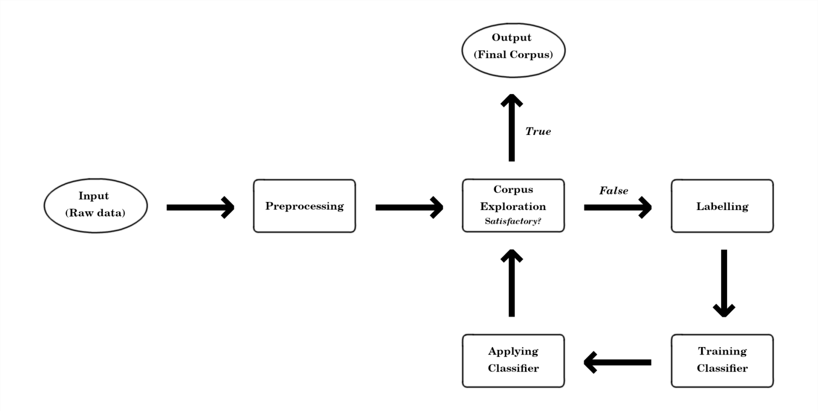

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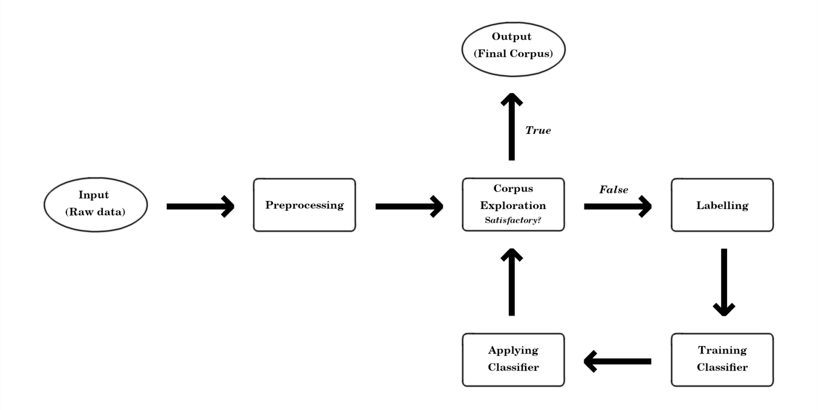

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- NB: it is important to ensure that we label a wide range of non-philosophy.

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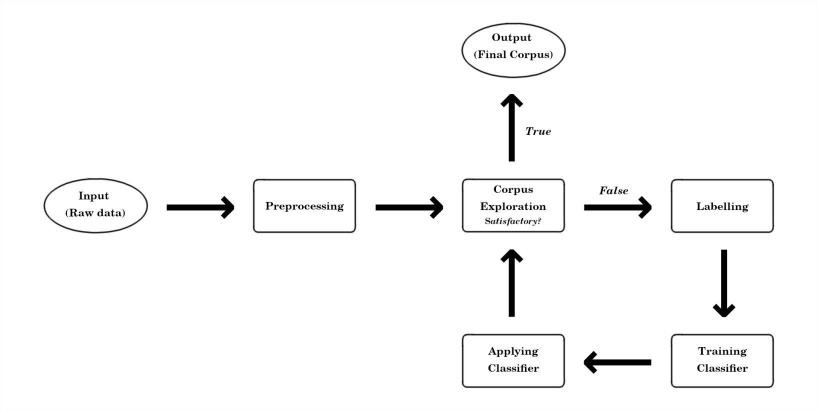

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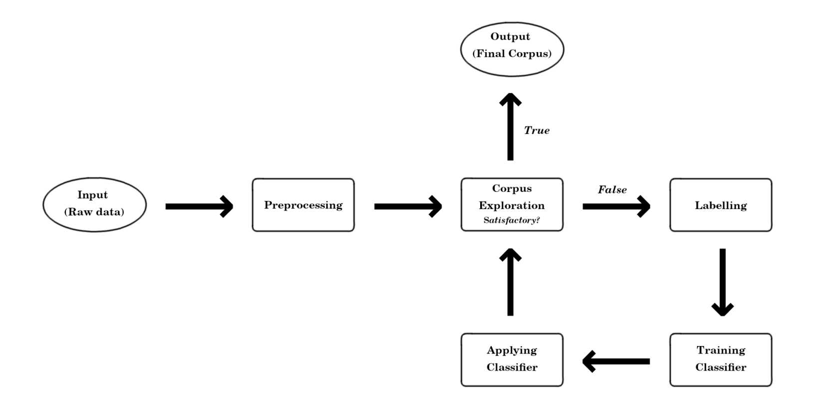
Corpus Construction Flow Diagram



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  - Stop when satisfied that the corpus does not contain too much ‘non-philosophy’

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- NB: term-term matrices can get very large. Various methods to control the size of the dictionary were employed.

RESULTS

Corpus Construction (Size Reduction)

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Classifiers become more selective:

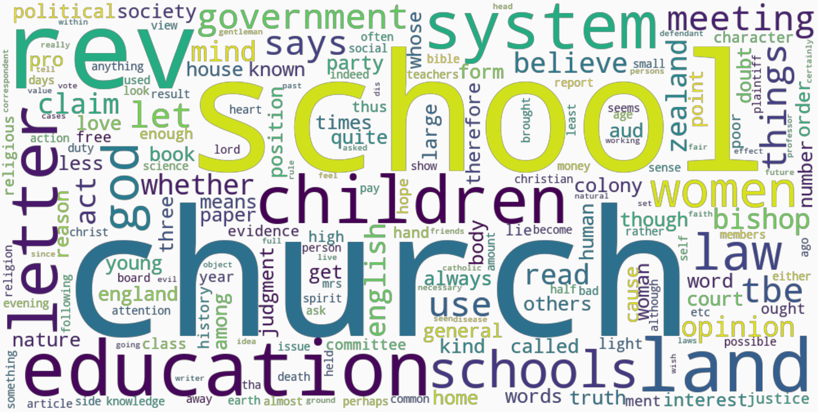
Corpus	Article Count
Processed dataset	7592619
(Step 0) 'philoso*' Corpus	29647
(Step 1) Naive Bayes 1	239649
(Step 2) Naive Bayes 2	31131

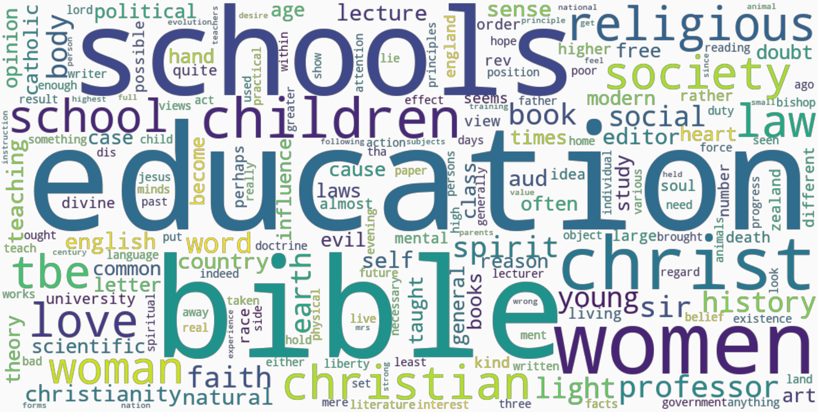
Table: Article counts for processed dataset and general philosophy corpora.

Word Cloud: Sample of Processed Dataset


race
hours
literary
press
sense
policy
university
yesterday
labour
board
influence
correspondent
committee
college
chief
love
return
gold
writer
important
gone
bank
study
prince
christian
article
whioh
messrs
action
books
faith
line
philosophers
professor
looked moment
religion
works
parliament
schools
mother
stated
cost
native
saturday
makes
monday
george
christ
fire
miles
rev
american
district
speech
council
happy
twenty
worth
god
yes
paris
likely
turned
melbourne
live
family
states
husband
north
cases
science
horse
knowledge
appears
association
evidence
married
railway
turn
change
subjects
road
ladies
duty
seemed
looking
religious
sunday
lord
feet
living
knew
air
river
health
bishop
object
boy
special
national
earth
natives
play
author
real
captain
reading
progress
story
dead
girl
trade
person
eyes
black
book
bill
working
editor
service
french
dunedin
west
lecture
paid
towards
scientific
saw
notice
tha
spirit
certainly
stand
aro
justice
british
women
miss
motion
island
dear
run
laws
sure
hard
ten
wish
local
colonial
white
modern
recently
father
king
bible
property
language
interesting
report
art
hia
queen
hall
member
child
club
questions
colonies
regard
philosophical
fellow
police
otago
condition
articles
judge
died
force
chair
value
charge
united
york
education
named
minister
replied
written
auckland
address
hair
alone
wellington
feel
social
german
occasion
france

WORD CLOUD: STEP 1




education
bible
schools
children
school
religious
society
christ
women
christian
law
social
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love
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tbe
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history
light
faith
natural
christianity
young
sir
spirit
self
earth
word
country
english
letter
common
scientific
university
teaching
catholic
opinion
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either
liberty
strong
least
kind
written
set
mere
literature
interest
three
facts
government
anything
land
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Labelling

Label	Step 1 Value	Count	Step 2 Value	Count
Readable	True	247	True	918
	False	26	False	41
Philosophy	True	101	True	299
	False	147	False	620
Philosophy Type	Religion-Science	58	Religion-Science	140
	Ethics-Politics	25	Ethics-Politics	94
	Epistemology-Metaphysics	3	Epistemology-Metaphysics	13
	Other	15	Other	52
Writing Type	Public Event	40	Public Event	97
	Letter to the Editor	23	Letter to the Editor	69
	First-order Writing	36	First-order Writing	111
	Review	2	Other	22
NZ	True	77	True	178
	False	12	False	41

Table: Label counts at Step 1 and Step 2.

Classifier Performance (Step 2)

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		Predicted	
		False	True
Actual	False	181	14
	True	15	62

Table: Confusion Matrix for Second Naive Bayes Classifier

- Accuracy: 0.89
- Precision: 0.81
- Recall: 0.80

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  - prevalence of ‘edge cases’ and mistaken labelling in the false positives.
- Conclusion: the performance of the classifiers is being limited by the quality of the labels.

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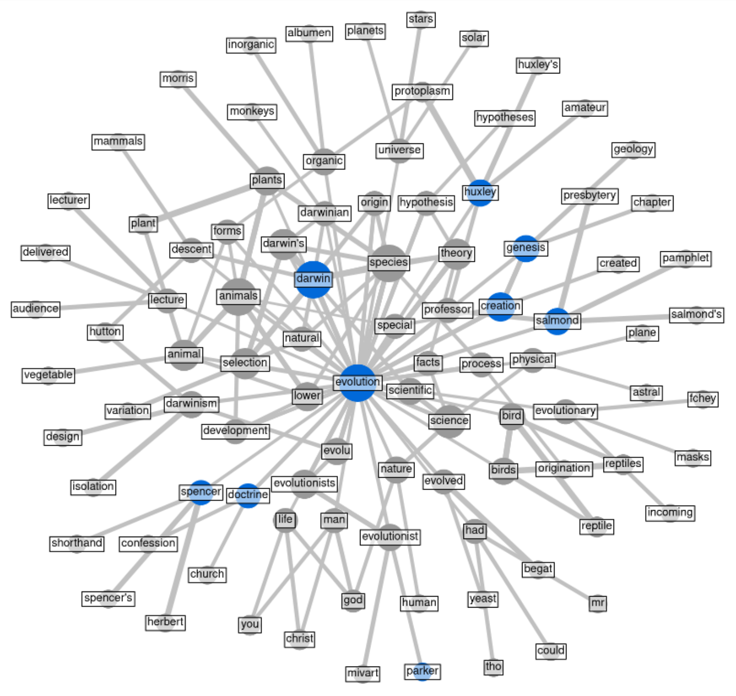
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solar
inorganic
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morris
protoplasm
monkeys
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plants
huxley
lecturer
origin
hypothesis
presbytery
chapter
darwinian
plant
forms
darwin's
genesis
delivered
descent
theory
species
created
pamphlet
darwin
animals
lecture
professor
creation
audience
salmond
salmond's
special
hutton
natural
plane
animal
selection
facts
process
physical
vegetable
evolution
scientific
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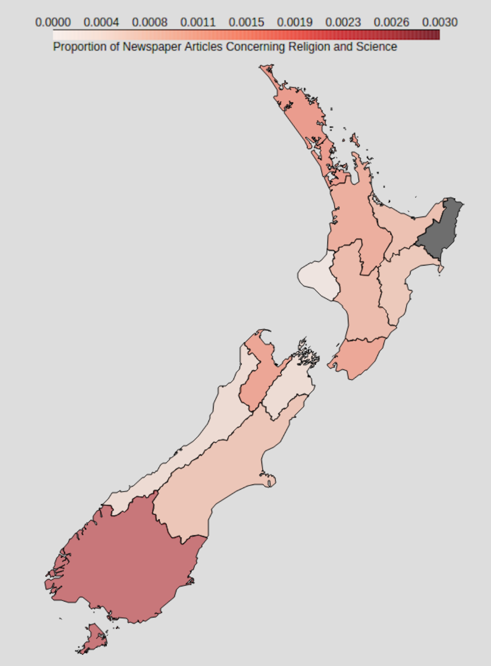
0.0000 0.0004 0.0008 0.0011 0.0015 0.0019 0.0023 0.0026 0.0030
Proportion of Newspaper Articles Concerning Religion and Science

UPSHOT

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2. The corpus produced at the corpus construction stage shows potential for research into early New Zealand philosophy.

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   - but with shortcomings to be aware of.

Links

- Dashboard: `nz-newspaper-philosophy.herokuapp.com`
- GitHub (full project): `github.com/JoshuaDavidBlack/NPOD_Philosophy`
- GitHub (dashboard): `github.com/JoshuaDavidBlack/NPOD_Philosophy_Heroku`