UofT 3666 – Applied NLP Final Project

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Introduction

- Project from Riipen, Deploy Software Solutions, Climate Change Study
- Deploy Software Solutions was interested in learning about NLP.
- In order to explore this, they are considering a situation that could have a positive impact and were interested in being able to automatically go through pdfs and extract wisdom that consumers could use.
- Interested in developing a consumer app, ideally highlighting information that would be personalized for the consumer and actions they can take to make a difference.

Problem Statement and Objectives

- The primary purpose of this project was to conduct a feasibility study.
- In order to solve this problem, there were three areas of focus:
  - PDF Extraction
  - LDA Topic Modelling
  - Identifying Actions
- Our objective were to:
  - Extract the data and explore various tools related to extraction.
  - Explore topic modelling and possible uses cases.
  - Explore and attempt to classify actions within the documents based on sentence structure.

Methodology

- After the Project Kickoff and acquiring the data
- Step 1: PDF Extraction
- Step 2a: Action Parsing and Classification
- Step 2b: LDA Modelling
- Step 3: Combine and Synthesize.

PDF Extraction

- Three different packages were tried: PyPDF2, PDFMiner, and Tika.
- Out of the three, we found Tika to be the best overall. PDF Miner was the best pure Python option.
- Objective was focused on implementation.
- When utilizing the tools, heuristics were applied in order to eliminate Unicode new line characters and tabs.
- Challenges and Issues:
  - PDFs can be formatted differently, this results in greater emphasis needed for preprocessing. For example, 1 column vs 2 columns.
  - The transcription can be poor and inaccurate.
  - Debugging. There were a variety of errors and challenges. Examples: Encrypted Files, Blank Pages.
  - Results vary across the different tools. Certain tools may work better on certain PDFs. This makes it difficult to standardize an approach.

PDF Extraction - PDF Miner

- Printed output of the text is fairly clean.
- One issue with PDF Miner is that it can be sensitive to document names.
- Another issue that can be seen is that some sentences are cut and split into two or three lines. This has the potential to be problematic depending on the context.

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Fundamentals of Chatbots

• A chatbot’s architecture, shown in Figure 9-2,

is

comprised of two primary components.
– The first component

is a user-facing interface that handles the
mechanics of receiving user input (e.g., microphones or a web API)
and delivering interpretable output (speakers or a mobile frontend).

– This outer component wraps the second component, an internal dialog
input, maintains an internal state, and

interprets text

system that
produces responses.

Fig-9.2: Architecture of a Chatbot

9
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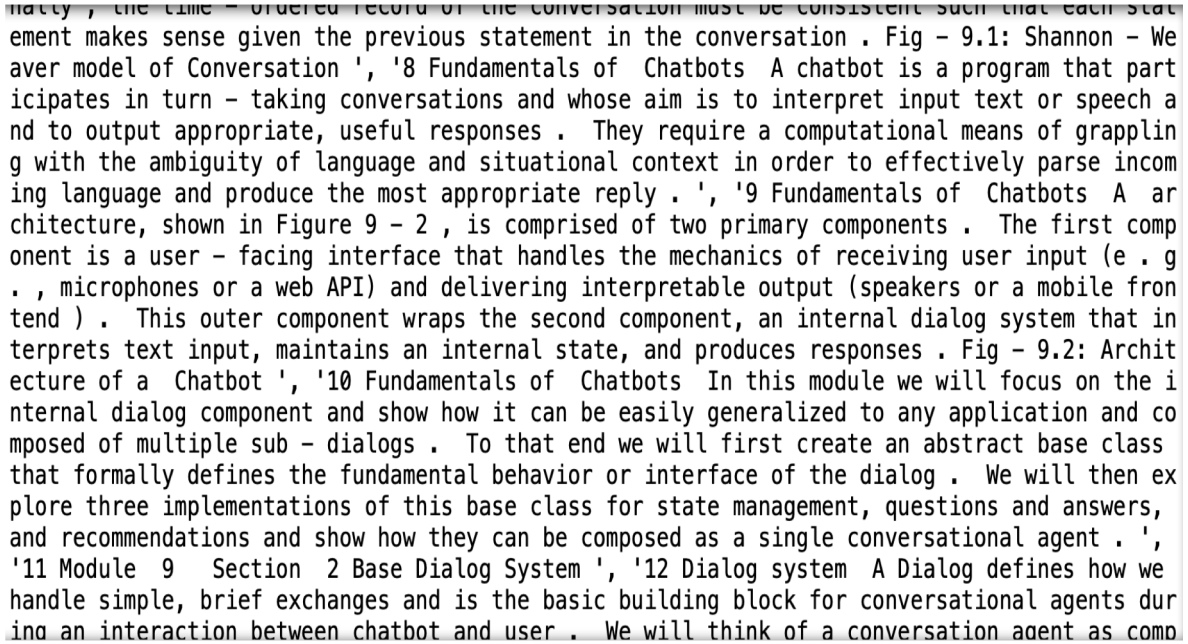
PDF Extraction - PyPDF2

- The output is a list of pages.
- When parsing the document, you end up having to go page by page.
- The raw output initially was messy. There were new line characters in between every token.
- Interesting aspect is dealing with encrypted files. For our purposes, we checked for encryption and skipped the encrypted documents.



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nally , the time - ordered record of the conversation must be consistent such that each stat
ement makes sense given the previous statement in the conversation . Fig - 9.1: Shannon - We
aver model of Conversation ', '8 Fundamentals of  Chatbots  A chatbot is a program that part
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ecture of a  Chatbot ', '10 Fundamentals of  Chatbots  In this module we will focus on the i
nternal dialog component and show how it can be easily generalized to any application and co
mposed of multiple sub - dialogs .  To that end we will first create an abstract base class
that formally defines the fundamental behavior or interface of the dialog .  We will then ex
plore three implementations of this base class for state management, questions and answers,
and recommendations and show how they can be composed as a single conversational agent . ',
'11 Module  9   Section  2 Base Dialog System ', '12 Dialog system  A Dialog defines how we
handle simple, brief exchanges and is the basic building block for conversational agents dur
ing an interaction between chatbot and user .  We will think of a conversation agent as comp
```

PDF Extraction - Tika

- The output is a string.
- Easy to use.
- Output here has new lines and tab characters stripped out.
- Requires an up to date Java Server.
- Parses the whole document at once. This makes it easy to use, however, it can be problematic if you only need specific pages or have a PDF document with a blank page.

a conversation, a participant can either be listening or speaking. Effective conversation r equires at any given time a single speaker communicating and other participants listening. – Finally, the time-ordered record of the conversation must be consistent such that each st atement makes sense given the previous statement in the conversation. Fig-9.1: Shannon-Wea ver model of Conversation 8 Fundamentals of Chatbots • A chatbot is a program that part icipates in turn-taking conversations and whose aim is to interpret input text or speech a nd to output appropriate, useful responses. • They require a computational means of grappli ng with the ambiguity of language and situational context in order to effectively parse in coming language and produce the most appropriate reply. 9 Fundamentals of Chatbots • A chatbot's architecture, shown in Figure 9-2, is comprised of two primary components. – The first component is a user-facing interface that handles the mechanics of receiving user inp ut (e.g., microphones or a web API) and delivering interpretable output (speakers or a mobi le frontend). – This outer component wraps the second component, an internal dialog system that interprets text input, maintains an internal state, and produces responses. Fig-9.2: Architecture of a Chatbot 10 Fundamentals of Chatbots • In this module we will focus on the internal dialog component and show how it can be easily generalized to any application and composed of multiple sub-dialogs. • To that end we will first create an abstract base c lass that formally defines the fundamental behavior or interface of the dialog. • We will then explore three implementations of this base class for state management, questions and a nswers, and recommendations and show how they can be composed as a single conversational a

Data

- There were two main components to our data.
  - A CSV containing a sample of the Action information.
  - PDFs containing Climate Change information.
- CSVs containing a sample of Action information.
  - Had 12 fields: actions, action_type, disaster_type_title, disaster_type_detail, doc_page, doc_path, doc_title, doc_publisher, date_added, contet_geography, context_usertype, notes
  - Contained about 1000 observations, of which 820 were citizen actions
- PDFs related to climate change
  - Approximately 50 pdfs.
  - 30% of the documents had been manually examined to create the CSV

Data Continued

- One of the challenges that we ended up facing was a small set of data.
- This proved to be problematic when applying Classifier Models or when applying an LDA model.
- One of the solution to this was to create additional data to enrich our dataset.
- Approximately 20 additional Climate Change pdfs were added.
- Another challenge was that we had examples of actions, but nothing to contrast them with. In order to have a balanced training set, we manually extracted 388 examples of non-actions from the PDFs, and then duplicated them, to approximately equal the number of action examples.

LDA

- Approach:
  - Started by using Sklearn and performing the LDA topic modelling.
  - Based off of the results of our topics, tested various combinations of topics and number of terms.
  - Moved on to try Gensim to perform topic modelling and get coherence scores.
  - Iterated to improve topics and scores by refining stopwords and increasing the amount of data.
- The best coherence score tested was with 3 topics and was -0.13 using the u_mass measure for coherence.

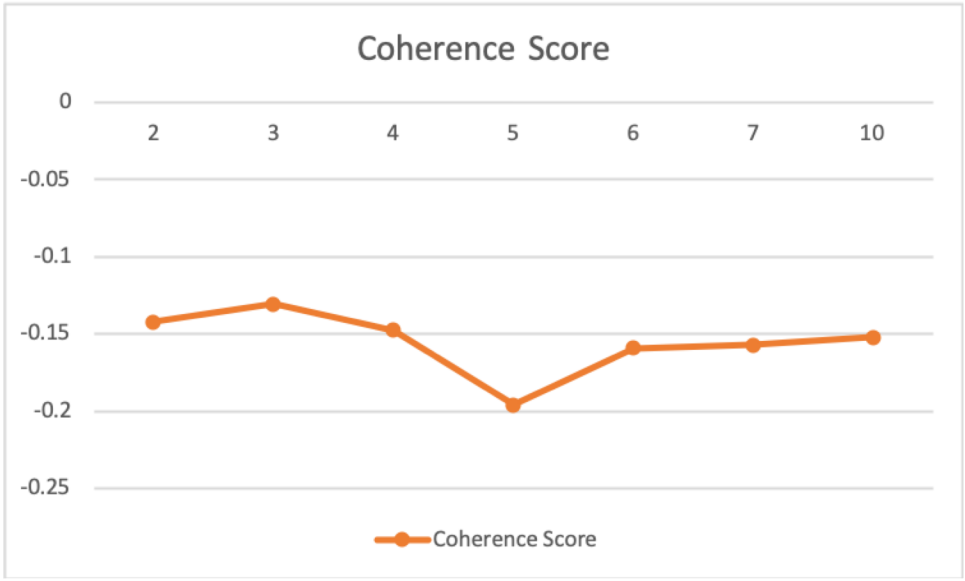
LDA

- Our best result across all the iterations had a coherence score of -0.13.
- It can be seen that the terms within the topics are close together and there are connections.
- An issue is there is overlap between the topics. This might indicate that there is not enough diversity amongst the topics.

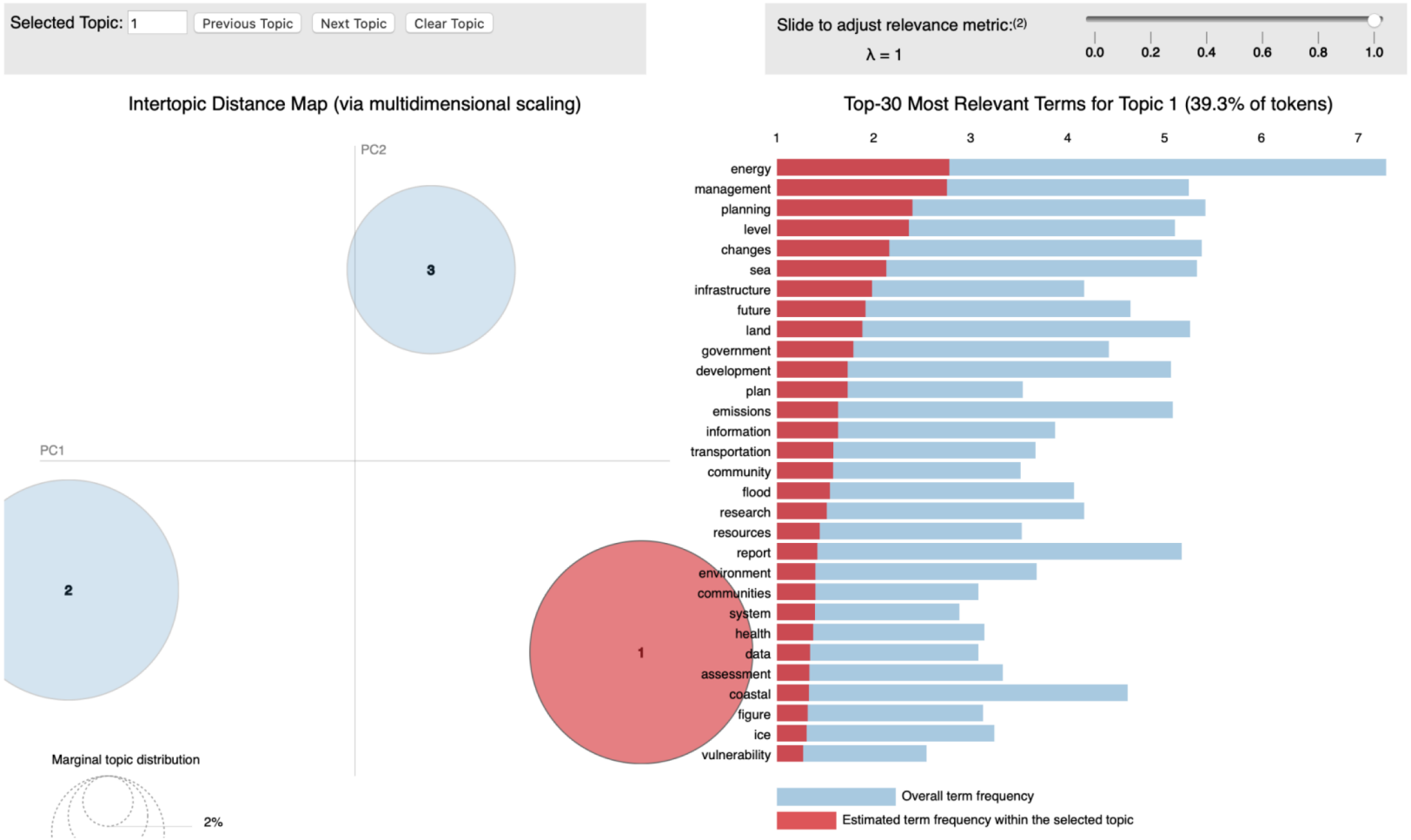
```
Number of topics: 3 Number of Terms: 10
[([(0.004631676, 'energy'),
   (0.0045930427, 'management'),
   (0.0039982614, 'planning'),
   (0.0039370125, 'level'),
   (0.003597411, 'changes'),
   (0.0035456615, 'sea'),
   (0.0033018345, 'infrastructure'),
   (0.0031888986, 'future'),
   (0.003135145, 'land'),
   (0.0029807717, 'government')],
  -0.11312160203614283),
 ([(0.005660018, 'energy'),
   (0.0044247587, 'report'),
   (0.004079819, 'emissions'),
   (0.0040084627, 'changes'),
   (0.0036828027, 'sea'),
   (0.0036512404, 'coastal'),
   (0.003472614, 'development'),
   (0.003346625, 'land'),
   (0.003226643, 'future'),
   (0.0030616391, 'research')],
  -0.12724002054886982),
 ([(0.0041694823, 'land'),
   (0.0039146347, 'planning'),
   (0.003820342, 'development'),
   (0.0035005992, 'energy'),
   (0.0034255798, 'report'),
   (0.003383334, 'coastal'),
   (0.0032530655, 'risks'),
   (0.0031254895, 'emissions'),
   (0.0030975, 'plan'),
   (0.0030801585, 'sea')],
  -0.1981268823302916)]
Random Document Distribution
[(0, 0.04762689), (1, 0.6231852), (2, 0.32918796)]
Coherence: -0.13066012318477496
```

LDA - Results

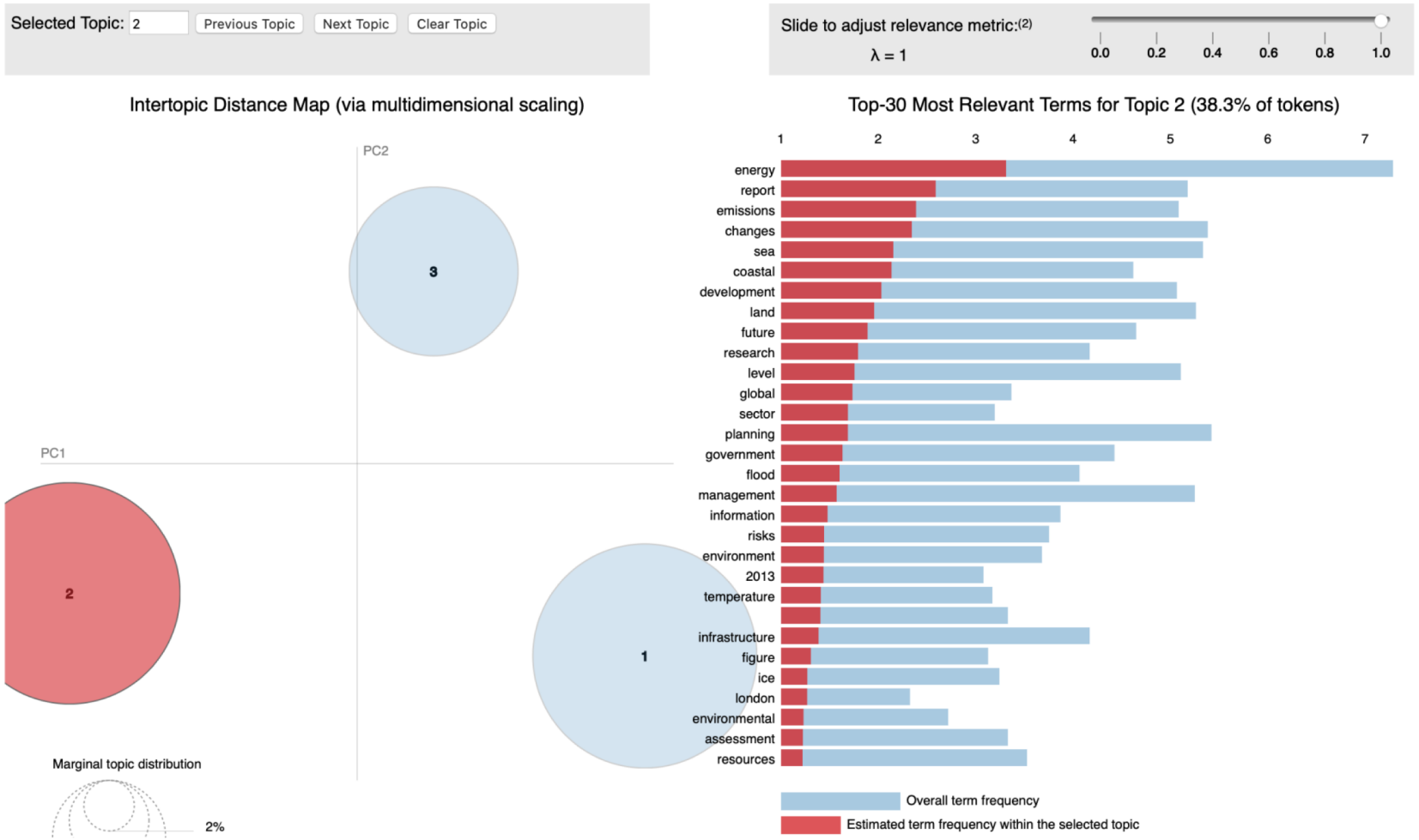
- Found that Coherence Score was better for a smaller number of topics, eventually score plateau.



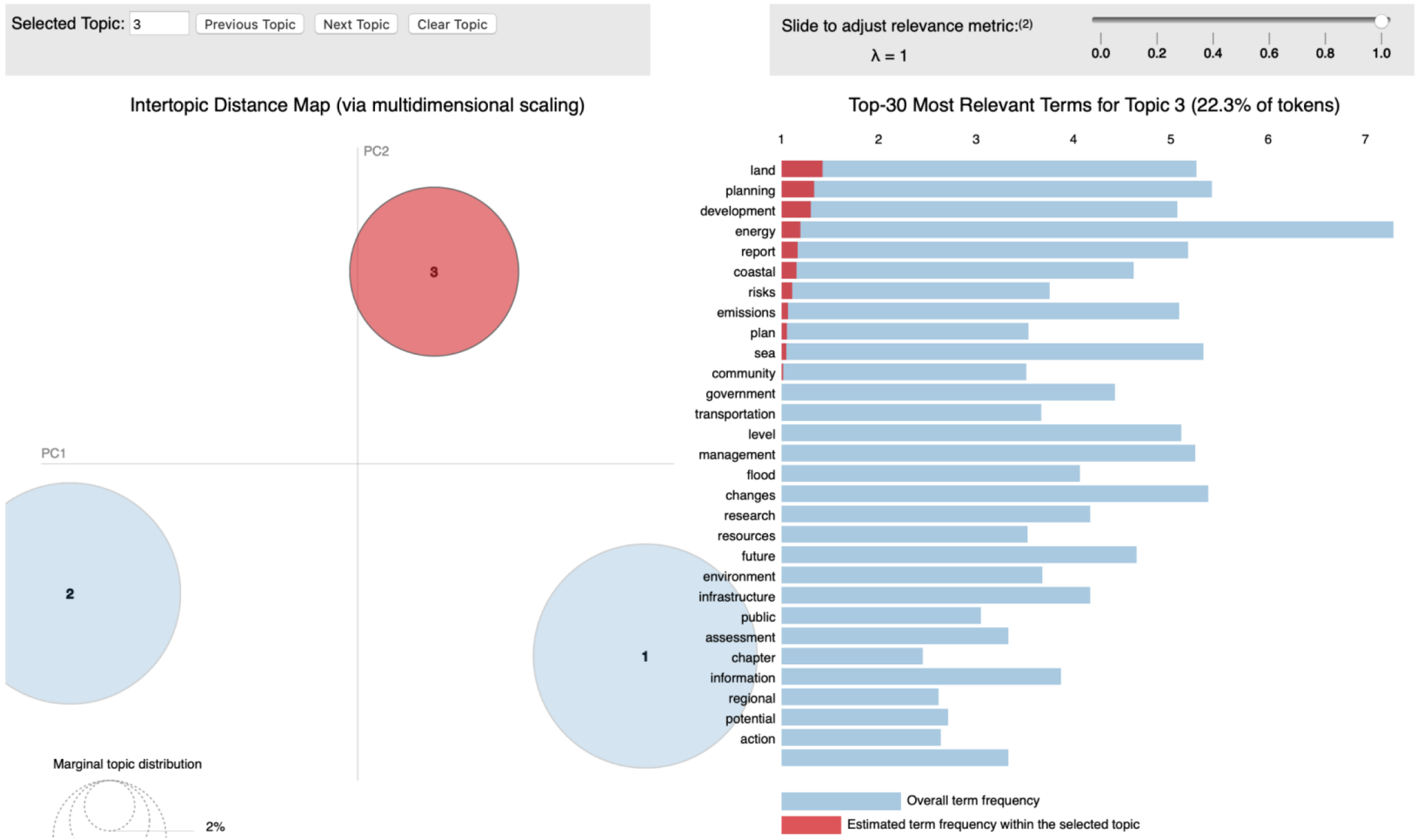
PyLDAvis - Topic 1



PyLDAvis - Topic 2



PyLDAvis - Topic 3



LDA Findings

- One of the challenges that was faced was that NLTK stopwords were reducing the corpus down.
- In order to stop this, a stopwords file was created and stopwords were defined based on examining the corpus tokens frequency distribution.
- Stopwords file included: common punctuation, common terms (canada, climate, change, http, www, com, and, or, etc), meaningless unicode characters (\uf0b7).
- In addition, a heuristic was applied in order to only include tokens whose length was greater than two.
- Another challenge faced was the: volume, quality, and similarity of data.
- There were documents that were similar, yielding closely related topics.
- We also found that when we added new documents to our corpus, that our coherence score improved.

Identifying Actions
Overview

Principle Task:

- From examples of ‘actions a citizen could do’, learn to automatically identify such actions.

Our Approach:

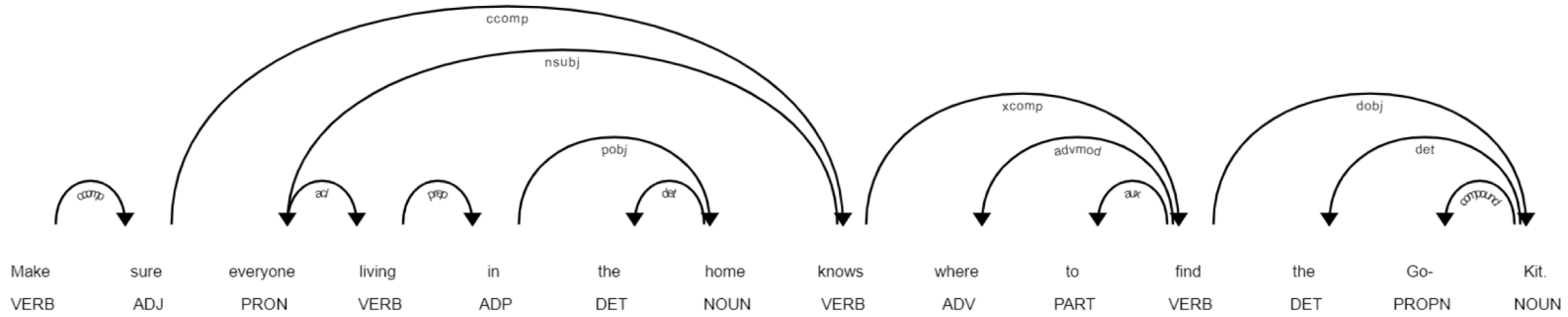
- Look at the grammatical structure of the sentence instead of the words.
- Consider both Machine Learning and Rule-Based algorithms.

Identifying Actions
Tools

- To capture the grammatical structure of the sentence, we considered:
  - nltk POS tagging - doesn't provide enough information for our purpose
  - CLiPS modality checker - buggy
  - Stanford CoreNLP - runs in Java, so more complicated to install
  - spaCy -
    - in Python
    - easy to use
    - produces dependency parses suitable for our purpose

Identifying Actions
Text to Grammatical Tokens

1. Extract the sentences from the text file with nltk sentence_tokenizer.
2. Parse the sentences into dependency parse trees with spaCy.



3. Represent the top two levels of the trees as lists of grammatical tokens.
   `['ROOT_self_VBP', 'LEFT_nsubj_PRP', 'RIGHT_xcomp_VB', 'RIGHT_punct_.']`
4. Use the grammatical tokens instead of words in your favourite algorithm.

Identifying Actions
Logistic Regression Classifier

1. Vectorize the sequences of grammatical tokens with TF-IDF.
2. Apply varying degrees of feature reduction with TruncatedSVD.
3. Train and test Logistic Regression model with 10-fold cross-validation.
4. Typical fold scores:

	precision	recall	f1-score	support
action	0.81	0.83	0.82	83
non_action	0.81	0.79	0.80	77
accuracy			0.81	160
macro avg	0.81	0.81	0.81	160
weighted avg	0.81	0.81	0.81	160

5. Best results were obtained without Truncated SVD.
6. Retrain the model on the entire training data.
7. Test on the held-out test data.

Identifying Actions
Manual Scoring of a Small Sample

Human	No SVD	SVD-5	Sentence
action:	action:	action:	Process Infrastructure Ports, Marine & Offshore Project No.
non_action:	action:	action:	This approach will minimize the initial costs of considering SLR, and the future costs of adaptation.
action:	action:	action:	Such infrastructure should be designed and constructed to remain operational during floods.
non_action:	non_action:	action:	1.16 Sea Dike System A system of: dikes, dunes, berms or natural shorelines that provide a similar fu
non_action:	non_action:	non_action:	We are especially grateful to the Government of Canada_s Climate Change Impacts and Adaptation Prograı
non_action:	non_action:	action:	Over the years since the United Nations Framework Convention on Climate Change was first signed in Ri
non_action:	non_action:	non_action:	The voices in my head that don_t want to be seen to always be a bother, that want to be liked, that a
non_action:	non_action:	action:	The loss of future timber supply presents a very significant challenge to the communities affected be
non_action:	non_action:	action:	Long-term climate records in the region indicated a significant warming trend, particularly in winter
action:	action:	action:	Use a list of suggested adaptation options and involve the workshop articipants in identifying a list
action:	action:	action:	Assess new information as it becomes available that could provide insight into or change best practic
non_action:	non_action:	action:	(2004); Jones et al.
non_action:	non_action:	action:	The judgments can be of at least two types, and are commonly a bit of both: that is, they may be issu
non_action:	non_action:	action:	From the viewpoint of adaptation and vulnerability reduction, these consequences are very important f
non_action:	non_action:	action:	SCD promotes economic gains while also facilitating social and environmental benefits.
non_action:	non_action:	non_action:	Technological approaches to adaptation include both _hard_ technologies such as capital goods and har
action:	non_action:	action:	(European Environment Agency, 2005) For example, no-till farming with residue mulching slows soil ero
non_action:	non_action:	action:	Davidson, P.R.
non_action:	non_action:	action:	Hogg and _. Meki.
non_action:	non_action:	action:	(2005) Adaptation Policy Frameworks for Climate Change: Developing Strategies, Policies and Measures.
non_action:	non_action:	action:	Climatic Change 61: 1-8 CANADIAN COMMUNITIES_ GUIDEBOOK FOR ADAPTATION TO CLIMATE CHANGE 99 guidebook
non_action:	non_action:	action:	How climate change is understood and talked about in Yukon is grounded in scientific evidence, the Tr
non_action:	non_action:	action:	A seventeen-year study of the vegetation communities on Qikiqtaruk-Herschel Island documented rapid c
non_action:	non_action:	non_action:	There are obvious economic benefits to going forward with a FireSmart Plus approach linked to biomass
non_action:	action:	action:	This local premium may be as high as two to four- fold over imported production._ (Serecon, 2007 P. A
non_action:	action:	action:	Mayo Region Climate Change Adaptaton Plan.
non_action:	non_action:	action:	Retrieved from: http://www.yukon-news.com/ RESEARCH NORTHWEST & MORRISON HERSHFIELD 40 Yukon _State o
non_action:	non_action:	action:	The project is part of the wider initiative, the BC Regional Adaptation Collaborative (RAC) to help c
action:	action:	action:	Planning can be initiated either through voluntary means or by regulation.
non_action:	non_action:	action:	Changes in air temperature and precipitation patterns are noticeably affecting our weather, water cyc
action:	non_action:	action:	_ Restore riparian and instream habitat.

Identifying Actions
Results on Held-Out Test Data

- Logistic Regression without Feature Reduction

Metric	Score
Accuracy	0.71
Precision	0.67
Recall	0.63
F1	0.67

- Logistic Regression with 5 Features

Metric	Score
Accuracy	0.35
Precision	0.26
Recall	1.0
F1	0.41

- In general, the more we reduced the number of features, the more the algorithm labelled everything an ‘action’.

Identifying Actions
Rule-Based Solution

- Obvious pattern visible in frequency counts of grammatical tokens for actions

```
[('ROOT_self_VB RIGHT_dobj_NN RIGHT_punct_.', 47),
 ('ROOT_self_VB RIGHT_dobj_NNS RIGHT_punct_.', 28),
 ('ROOT_self_VB RIGHT_dobj_NN RIGHT_prep_IN RIGHT_punct_.', 18),
 ('ROOT_self_VB RIGHT_acomp_JJ RIGHT_punct_.', 17),
 ('ROOT_self_VB RIGHT_prep_IN RIGHT_punct_.', 17),
 ('ROOT_self_VB RIGHT_dobj_NN RIGHT_cc_CC RIGHT_conj_VB RIGHT_punct_.',
 ('ROOT_self_VB RIGHT_dobj_NN RIGHT_advcl_VB RIGHT_punct_.', 9),
 ('ROOT_self_VB RIGHT_cc_CC RIGHT_conj_VB RIGHT_punct_.', 9),
```

- Created simple hard-coded rule

```
if candidates[i][0] == 'ROOT_self_VB' and candidates[i][1].startswith('RIGHT_dobj_NN'):
```

- Results on held-out test data

Metric	Score
Accuracy	0.85
Precision	1.0
Recall	0.77
F1	0.87

- For this specific task, a one-line rule was the best performer.

Challenges

- Data Variability
  - PDF documents were not in consistent format.
  - PDF extraction and preprocessing is labour intensive.
  - PDF extraction tools themselves are fairly easy to use, dealing with the output and wrangling it to a useable format can be difficult and imprecise.
- Amount of data
  - In order to deal with a smaller dataset, time was spent in order to enrich it.
- Monolithic data
  - Many documents were large and covered many topics. This made it more difficult to distinguish individual topics from each other.
- Human Scoring Bias
  - It was difficult to remain objective in the manual scoring of the test results at the end, after having worked with the data and models for a long time.

Lesson Learnt

- Better to work with a larger dataset.
- PDF extraction was a valuable exercise. PDFs can be difficult to work with and the results from the different tools will vary.
- It is better to use fewer topics. Noticed that fewer topics had a better Coherence Score, eventually the score plateaus.
- LDA is not a very good tool for small datasets.
- Parsing sentences into grammatical structure can yield good results for some problems.
- Sometimes a hard-coded rule can be the right tool for the job.