#### **CAN Treaties – Methods Overview**

Using String Kernels: When we use string kernels to measure the similarity between two texts, we look at common sequences of characters. Using the term "majesti" as an example, with a specified length of 5 characters:

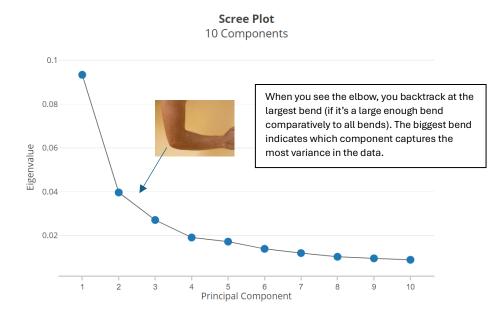
- 1. **Split** "majesti" into all possible 5-character sequences (substrings):
  - a. "majes"
  - b. "ajest"
  - c. "jesti"
- 2. Compare Substrings: We compare these 5-character sequences with the 5-character sequences from another text.
  - a. e.g., if the other treaty text also has "majesty", it would have the same substrings:
    - i. "majes"
    - ii. "ajest"
    - iii. "jesty" (which shares "jesti" with "majesti")
- 3. **Count Common Substrings**: We count how many of these 5-character sequences are common between the two texts. The more common sequences they have, the more similar the texts are considered to be.

Ultimately, this is how we get the graph(s) of the "thing" we want to look at – the overall theme or commonality across all the treaties – because we've computed the **Kernel Principal Component Analysis (KPCA)**. For Spirling this was harshness.

### How many "things" are there? - we can argue for 1 or 2:

Arguably, we are looking for a 1st and a 2nd component:

- **Eigenvalues**: indicates the amount of variance in the data that is explained by its corresponding principal component.
  - Higher eigenvalues mean that the principal component captures more variance from the data.

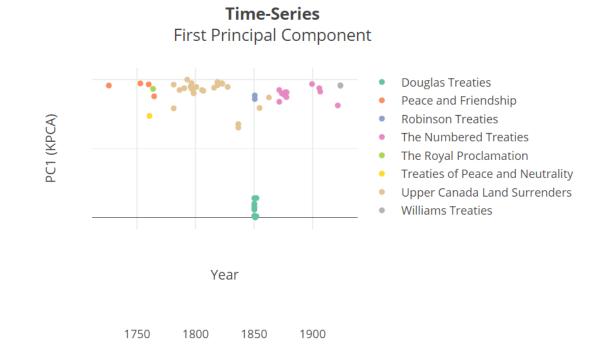


# Component 1 Graph - "the main thing":

 If you draw a trend line across each of the treaties is fairly stable outside of the Douglas Treaties (slight dip around 1850s).

There's some validation of this "main thing" trend in work by **Feir et al. (2023)** who did sentiment analysis on a sample of Canadian treaty texts.

- "The length of treaty texts increased over two centuries of historical treaty-making, while the average sentiment in the treaty texts remained relatively constant, contrasting the changing sentiment in agreements between Indigenous nations and the United States during this same period."



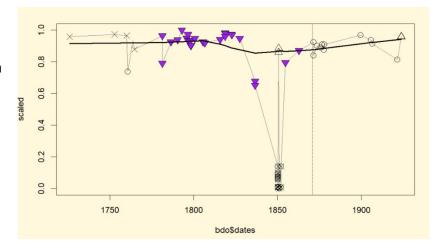
Arguably, when looking at word importance (below) we're seeing consistency in language, possibly due to the fact that Canada remained attached to the British (vs. American independence). This 1<sup>st</sup> component could reflect crown involvement ("surrend"ing to "majesti"; "becom"ing "subject"s; "commission" involvement) – although interestingly, "white" is an important distinguisher.

1

0.5

0

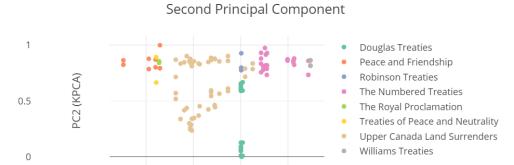
- This is our **Messy Graph 1** (mirrors Spirling's visual) with a trendline.
  - We'll be working on adjusting these graphs in a way that can clearly distinguish each individual treaty in a more visually appealing manner.



## Component 2 Graph - the "secondary thing":

- This component is more of a mystery (see word importance below).

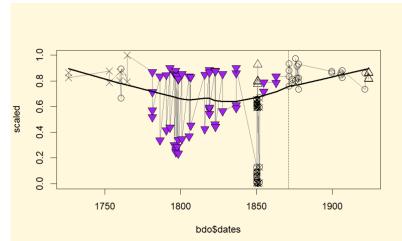
**Time-Series** 





Here's the "loadings" of each treaty on each of the "things".

- e.g., Referring back to the 1<sup>st</sup> graph (p. 2) the Douglas Treaties (DT01-DT10) are *all* very low on KPC 1 ("main thing").
  - Hence the green dots appear at the bottom of that graph.



1	Treaty	KPC1 Score	KPC2 Score
2	DT01.txt	-1.805939295	-0.757759895
3	DT02.txt	-1.071957768	-0.588192455
4	DT03.txt	-1.660291693	-0.542594024
5	DT04.txt	-2.114739514	-0.780190148
6	DT05.txt	-1.664173292	-0.479384933
7	DT06.txt	-2.316421396	-0.781109101
8	DT07.txt	-1.809882909	-0.829460649
9	DT08.txt	-2.0779433	-0.866227488
10	DT09.txt	-2.285623464	-0.864577987
11	DT10.txt	-2.698021539	-0.827409912
12	DT11.txt	-1.933846074	-0.271300189
13	DT12.txt	-2.94369106	-0.742106516
14	DT13.txt	-3.02916917	-0.72253333
15	PF01.txt	2.80444319	1.330688558
16	PF02.txt	2.783729121	1.350246077
17	PF03.txt	1.96052126	1.219802883
18	PF04.txt	2.035523878	1.763186146
19	RT01.txt	2.333115289	0.674901634
20	RT02.txt	2.06597273	0.373810102
21	NT1001.txt	2.077765088	2.137342434
22	NT101.txt	2.099417879	1.732886955
23	NT1101.txt	2.002294882	1.850719755
24	NT201.txt	2.297879254	1.38725355
25	NT301.txt	2.003271098	1.415544125
26	NT401.txt	2.03522479	1.159501644
27	NT501.txt	2.035583326	0.89999058
28	NT601.txt	1.893508784	1.035726057
29	NT701.txt	1.586139384	1.451852376

30	NT801.txt	1.136616258	2.510567299
31	NT901.txt	1.083016182	2.008435989
32	RP01.txt	0.814985275	1.056943555
33	TPN01.txt	-0.07808634	1.798424343
34	UCLS01.txt	0.180702587	-0.507366387
35	UCLS02.txt	1.205600699	-0.855465498
36	UCLS03.txt	0.856365642	-2.141594265
37	UCLS04.txt	0.843057714	-1.550028808
38	UCLS05.txt	1.151524218	-1.38706171
39	UCLS06.txt	0.727962902	-2.351893106
40	UCLS07.txt	0.505677978	-2.421121864
41	UCLS08.txt	0.21574232	-2.018717748
42	UCLS09.txt	0.594539368	-2.569337535
43	UCLS10.txt	0.246342411	-2.662392678
44	UCLS11.txt	-0.053964966	-2.712946623
45	UCLS12.txt	0.131702736	-1.877420133
46	UCLS13.txt	-0.110170069	-1.70523296
47	UCLS14.txt	-0.244868996	-1.079909157
48	UCLS15.txt	-0.197212933	-1.265845056
49	UCLS16.txt	-0.022725131	-0.120466124
50	UCLS17.txt	-0.133823501	-0.358277834
51	UCLS18.txt	-0.363767622	0.027117047
52	UCLS19.txt	-0.3697459	-0.897702799
53	UCLS20.txt	-0.492446814	-1.017909268
54	UCLS21.txt	-0.737304235	-0.120741353
55	UCLS22.txt	-2.59121508	2.027620146
56	UCLS23.txt	-2.85533955	2.354146889
57	UCLS24.txt	-2.021616009	1.566145754
58	UCLS25.txt	-1.62217179	1.92189358
59	WT01.txt	-1.145200535	1.790566166
60	WT02.txt	-1.2568663	1.828963885

#### How do we figure out what the "things" are? - we combine 2 methods:

- 1. Vector-space analysis: interpret string kernels directly
  - We've done this already to determine the **KPCA**, but we could analyze the string kernels directly. However, academics add on a 2<sup>nd</sup> method to interpret string-kernels because it provides more nuance. Thus, we add in...
- 2. Term Document Matrix conversion (stemming, etc.)
  - o Take the words and break them up into root components.
  - o Eliminate common words (said, the, etc.)
  - o Remove sparse terms (in our case, if the words don't appear in 90% of documents they aren't considered).
  - o Remove punctuation.

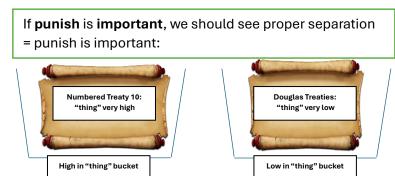
The argument is that using string kernels gives a more accurate *overall* representation of what the things are – because when you use **string kernels** the algorithm *preserves and considers the order that word appear in*. However, it's easier to add on a **TDM-IDF** process to assess each word's importance in a vacuum.

- Once we've stemmed, removed common words, etc. we feed them to two algorithms – **Random Forest** (Spirling) and **xgboost** (new age extremely powerful competition-winning predictive algorithm that uses Random Forest and **Gradient Descent**).

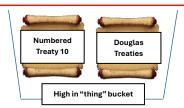
#### **Importance Algorithms:**

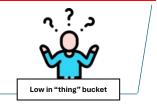
- (1) Random Forest: you can think of the entire sample of the treaties as the "forest". The algorithm plants 500-2000 "trees" at random points (word stems) in each treaty. Each tree makes a predictive "bucketing" decision (simplified below) extending throughout the entire corpus before the algorithm aggregates its calculations.
  - o e.g., Planting a "punish" tree: In Numbered Treaty 10, "punish" might occur frequently, indicating it is high in the "thing." Conversely, the Douglas Treaties might have few occurrences of "punish," indicating they are low in the same "thing."
    - The algorithm then asks: "If we split the treaties based on the occurrence of 'punish,' do they fall into the correct buckets?"

Numbered Treaty 10 SHOULD go into the bucket of "treaties high in thing," and the Douglas Treaties would go into the bucket of "low in thing."



If **punish** is **not important**, we might see inaccurate separation; we already know Douglas Treaties are low in thing, but "punish" is putting them in the wrong bucket = punish not important:





- (2) XGBoost: Extreme Gradient Boosting builds a model in a stage-wise fashion, where each new tree corrects errors made by previous trees.
  - o XGBoost starts with a simple initial model, perhaps predicting the average value of "thing" across all treaties.
  - o It calculates the difference (residual) between the actual values of "thing" (e.g., occurrences of important terms) and the predictions made by the initial model for each treaty.
    - A new decision tree is created to predict these residuals.
- e.g., Planting a "punish" tree:
  - o If "punish" appears often in a treaty, the tree might predict a higher residual (indicating the initial model underestimated the "thing" for this treaty).
  - o If "punish" is rare, the tree might predict a lower residual (indicating the initial model overestimated the "thing").
- The predictions from this new tree are added to the initial model to improve its accuracy.
  - This process of calculating residuals, creating new trees, and updating the model continues iteratively, with each new tree focusing on the remaining errors from the previous iteration.

Random Forest - KPC1: Term

majesti

o The final model is an ensemble of all the trees, where each tree contributes to refining the predictions.

# Algorithm Results – KPC1 ("main thing"):

 Here we have a graph of the most important features from KPC1 (the words that best separate the treaties into the correct "main thing" buckets), and the corresponding algorithms scores.

Top 35 Important Features in Random Forest Model



4.068352044

xgboost - KPC1: Feature

maiesti

Cover

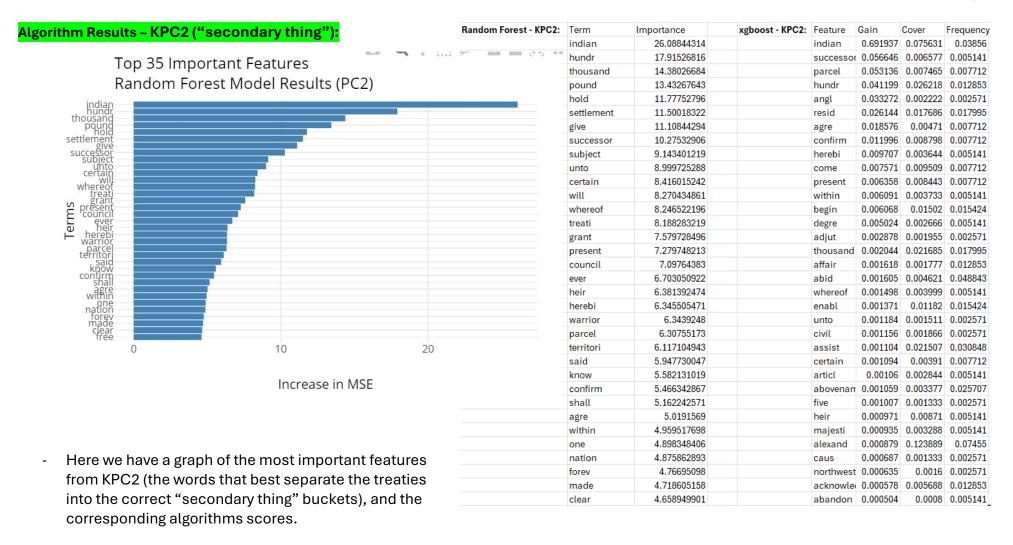
0.470726 0.041197 0.020045

0.000274 0.001421 0.004454

Importance

17.20697585

majesti surrend				
surrend				
treati subject becom fort				
subject				
becom-				
forț				
land				
nation				
said				
properti white children territori				
white				
children				
territori				
promis				
mark				
v island —				
⊆ subscrib				
promis promis mark sulsand subscrib year number				
Ψ number				
year year number claim within				
within				
men				
know hunt				
man				
IIIdy				
hogin				
bring				
noon				
understood begin bring peopl fifti				
indian villag ever sale				
villag				
ever				
cale				
Sale		_	4.0	4.5
	0	5	10	15
		Increase in	MCE	
		increase in	IVIDE	



Note on Term Importance: we spent weeks verifying that the calculations are accurate, double checking Spirling's methodology.

- Happily, Feir et al. (2023) the sentiment analysis paper also calculated term importance scores on Canadian treaties.
  - o I only wish I had found the paper sooner it would've saved hours of late nights and incessant worry.

### Component ("thing") Correlations:

When **stemming** words, we erase word suffixes to obtain the "root" of the word.

**Word stems with a high positive correlation** appear more frequently/are more prominent in treaties that have high scores on the principal component.

- These stems are characteristic of whatever "thing" the KPC is capturing when it scores high.

**Word stems with a high negative correlation** appear more frequently or are more prominent in treaties that have low scores on the principal component.

- These stems are characteristic of treaties that represent the opposite end of whatever the "thing" we've captured is.

Word Stem correlations can be treated as Kernel Principal Component Loadings – how much each word affects the "thing(s)".

There are 3677 terms captured in the documents (which we have the correlations for) so I'll just include the most important ones for each of KPC1 & KPC2.

KPC1:

Correlations - KPC1:	Positive Term Frequency		Correlation	Negative Term	Frequency	Correlation	
	majesti	42	0.75032493	lie	33	-0.548407	
	subject	23	0.60185895	consent	30	-0.553658	
	promis	28	0.5733319	former	23	-0.560293	
	subscrib	16	0.55606724	surrend	40	-0.567575	
	indian	45	0.55445765	small	28	-0.587325	
	observ	17	0.55082493	condit	26	-0.588202	
	conduct	15	0.54632025	deed	19	-0.588756	
	treati	22	0.54610993	except	32	-0.589300	
	conclud	21	0.53462359	proper	28	-0.614528	
	gracious	16	0.5209063	eight	35	-0.629332	
	obtain	16	0.50829347	committe	21	-0.630338	
	taken	14	0.50816445	howev	25	-0.633039	
	cede	17	0.50321271	token	14	-0.63999	
	perform	15	0.50107137	agent	24	-0.642289	
	stipul	13	0.47663875	dougla	13	-0.6451	
	deliber	11	0.47540714	sale	25	-0.645728	
	right	33	0.474763	deputi	29	-0.652682	
	bounti	11	0.4697672	understand	16	-0.65656	
	deal	11	0.46719	kept	19	-0.65774	
	behav	11	0.46600849	field	16	-0.67213	
	strict	17	0.4657789	unoccupi	13	-0.67427	
	proport	14	0.46491511	villag	21	-0.67643	
	behaviour	10	0.45646489	fisheri	17	-0.67845	
	immigr	10	0.44796383	white	32	-0.68125	
	obey	10	0.44660683	survey	25	-0.686672	
	school	10	0.4369626	understood	22	-0.693020	
	solemn	15	0.42870286	properti	39	-0.705774	
	assur	11	0.42469754	children	30	-0.70968	
	accept	15	0.42457366	land	53	-0.73535	
	dominion	14	0.36452071	becom	32	-0.744368	

KPC2:

Correlations - KPC2:	Positive Term Frequen	су	Correlation	Negative Term	Frequency	Correlation
	indian	45	0.73625333	appurten	14	-0.4066091
	treati	22	0.6003013	languag	9	-0.4110095
	govern	19	0.57026647	certain	32	-0.4348608
	commission	13	0.55899732	absolv	4	-0.4351349
	council	23	0.55440436	princip	26	-0.4422135
	subject	23	0.54270485	dispos	21	-0.4457174
	proceed	15	0.53347524	consider	36	-0.4691596
	punish	13	0.53154849	execut	21	-0.4718961
	obtain	16	0.53098622	deputi	29	-0.4720265
	travel	12	0.52135228	deliveri	9	-0.4774989
	conduct	15	0.51494313	clear	12	-0.4864373
	upon	27	0.5125373	seven	24	-0.4885747
	meet	12	0.50906024	present	42	-0.4892227
	minist	10	0.50759944	rehears	5	-0.5042469
	territori	18	0.50437313	situat	38	-0.5051159
	infring	12	0.49922643	forev	30	-0.5096283
	assum	13	0.49919554	descend	10	-0.5181152
	matter	13	0.49362828	begin	27	-0.5320179
	defin	12	0.49314839	pretend	6	-0.5355966
	assur	11	0.49196637	renounc	6	-0.5355966
	report	10	0.49152494	instrument	13	-0.5512711
	possibl	11	0.49048868	grant	29	-0.5518602
	interfer	14	0.48868337	whereof	46	-0.5623836
	dominion	14	0.48852598	emolu	7	-0.5631035
	request	18	0.48746437	greet	8	-0.5671626
	offend	13	0.48725998	parcel	19	-0.5720966
	negoti	13	0.48190129	warrior	10	-0.5812067
	advis	10	0.47961758	nation	26	-0.6003893
	appoint	18	0.47625332	receipt	14	-0.6115586
	notifi	13	0.47618779	successor	34	-0.6136265
	observ	17	0.47335551	confirm	27	-0.6140772
	school	10	0.46710603	heir	29	-0.6252556
	perform	15	0.46287027	unto	27	-0.6782567
	requir	16	0.46188875	hundr	54	-0.6921874

### e.g., Assessing the Treaties with Highest & Lowest Treaties values of KPC1:

#### **Highest: Numbered Treaty 10 (1906)**

- Content Focus: Extensive detailing of land cession, rights, and specific provisions for the Indigenous populations involved.
- Nature of Agreement: Specific commitments on both sides.
  - Outlines detailed rights to hunting, trapping, fishing, and the setup of reserves, as well as educational and agricultural support.
- **Rights and Compensations**: Clear definitions of compensations and rights, including annual payments and provisions for chiefs and headmen.

#### **Lowest: Douglas Treaties (1850)**

- Content Focus: Direct cession of land with fewer detailed rights or compensations.
- **Nature of Agreement**: Simplistic, primarily focusing on the surrender of lands with minimal protections or guarantees for the Indigenous populations beyond retaining village sites and some fishing and hunting rights.
- Rights and Compensations: Limited to one-time payment with no ongoing support or detailed rights enumerated for the future.

**Note:** Our search function web app that accesses where the word stems fall in treaties is operational.