Supervised signal-features learning from cyber-text and novel deep learning techniques for fine-grained cyberbully classification

Defence Presentation

Junaid Iqbal Khan

Department of Electronics & Information Engineering
Korea Aerospace University, South Korea

Key Original Concept at a Glance

Problem Statement

Previous Approaches

To classify texts into different classes of cyberbullying by taking a different approach from standard **embedding** (word or text embedding) **extraction-sequential model** setup, which are prone to their own challenges

Contribution

Signal Features

Developed a new method of extracting **"signal features"** from texts

-Signal features are sparse in Fourier domain, while smooth and dense in time domain.

-On the other hand, **word and text embeddings,** they are vector representation of text, but show characteristic of being either sparse or non-smooth in time domain.

Proposed Models

Proposed 3 **new deep learning models** for **classifying cyberbully types**

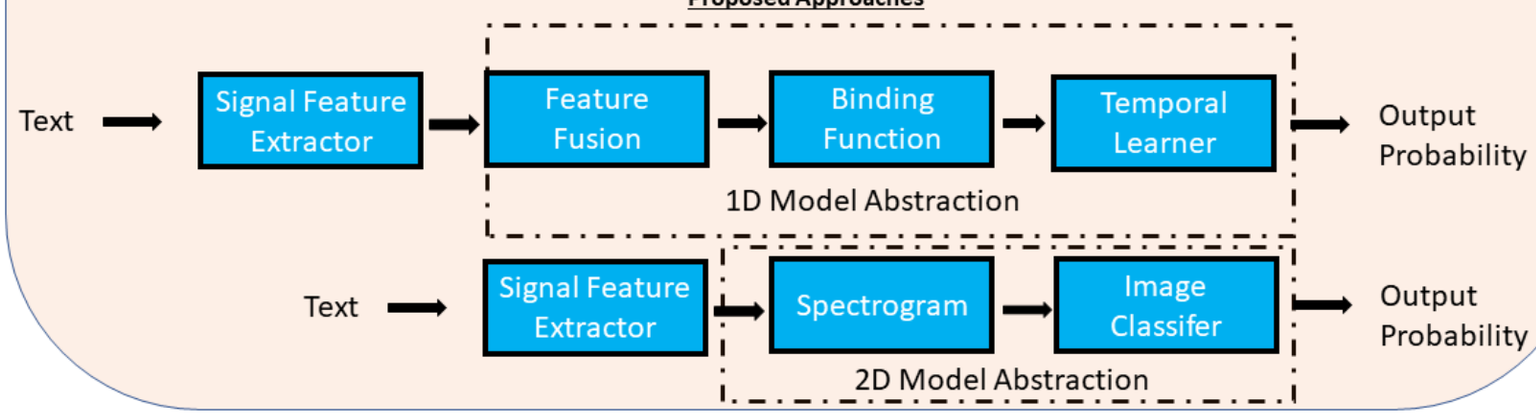
-They are based on novel combination of **Graph neural network, Transformer, WaveNet** and **PatchConvNet** architecture

- Two models focus on **1D input topology** and one model focuses on **2D input topology**

Evaluation

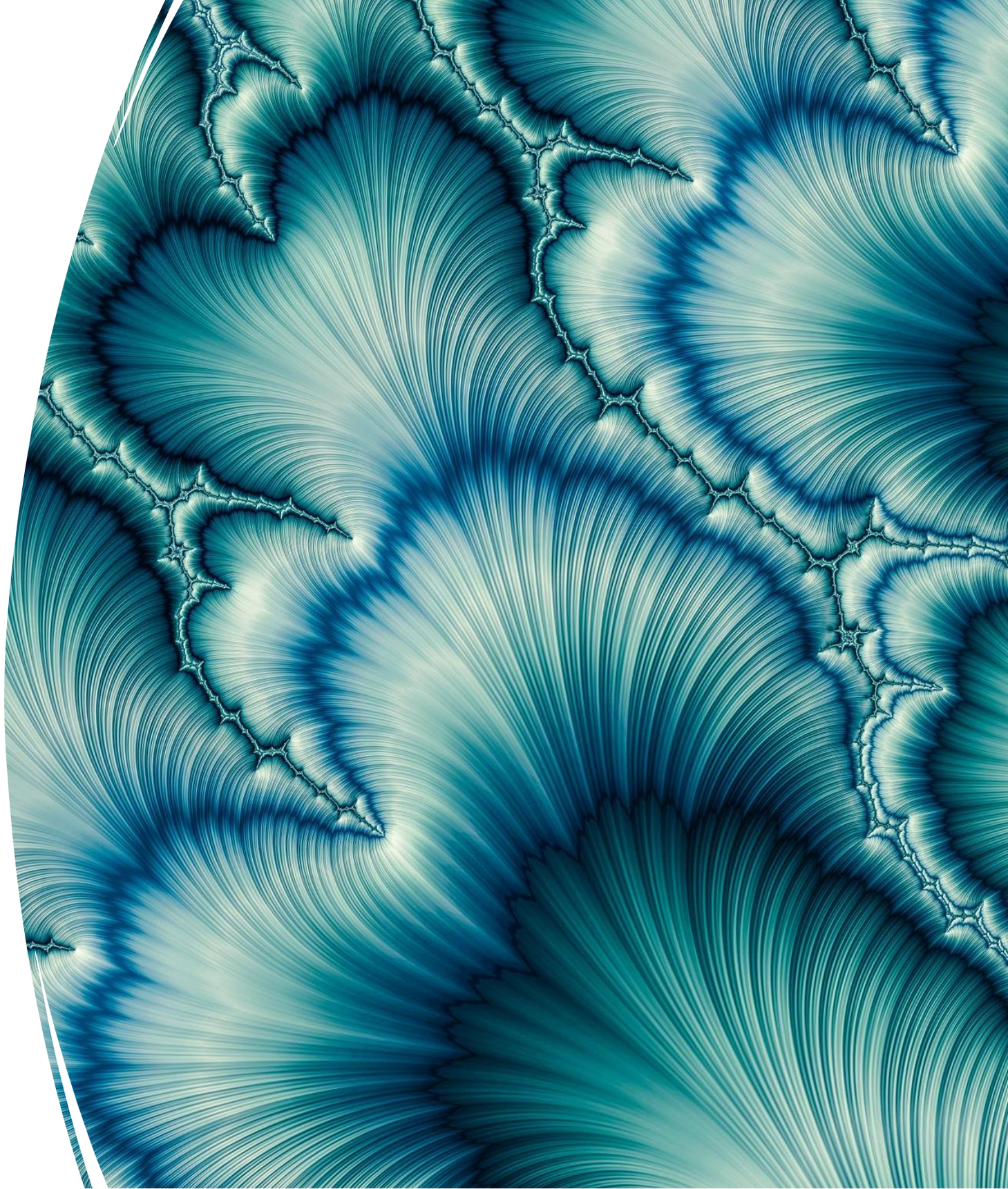
To show that these models **excel state of the art methods** in terms of greater accuracy at expense of lesser number of parameters

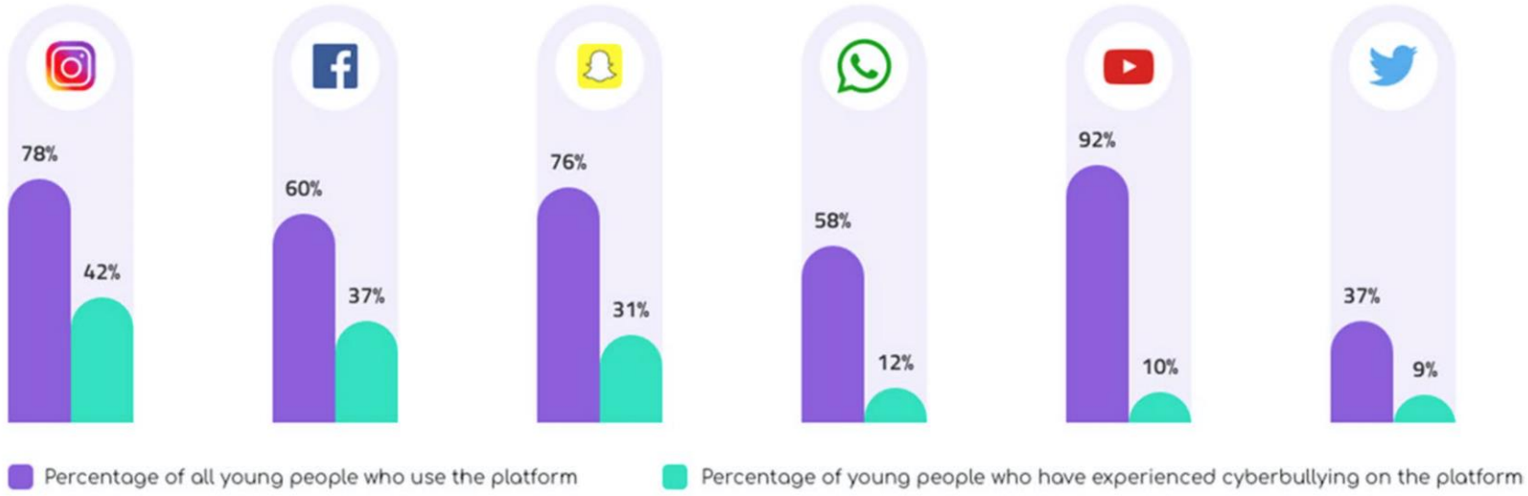
Proposed Approaches



Contents

- **Introduction**





Statistics on social media platforms where cyberbullying occurs [1]

Perspective

reddit

Machine Learning

API [2]

Net Nanny®

Kaspersky Safe Kids

KIDS

MOBILESPY® SMARTPHONE MONITORING SOFTWARE

Lexical Filtering

Commercial Softwares

Current Social Media Cyberbully Detection Platforms

Microsoft's Twitter AI Chatbot "Tay"

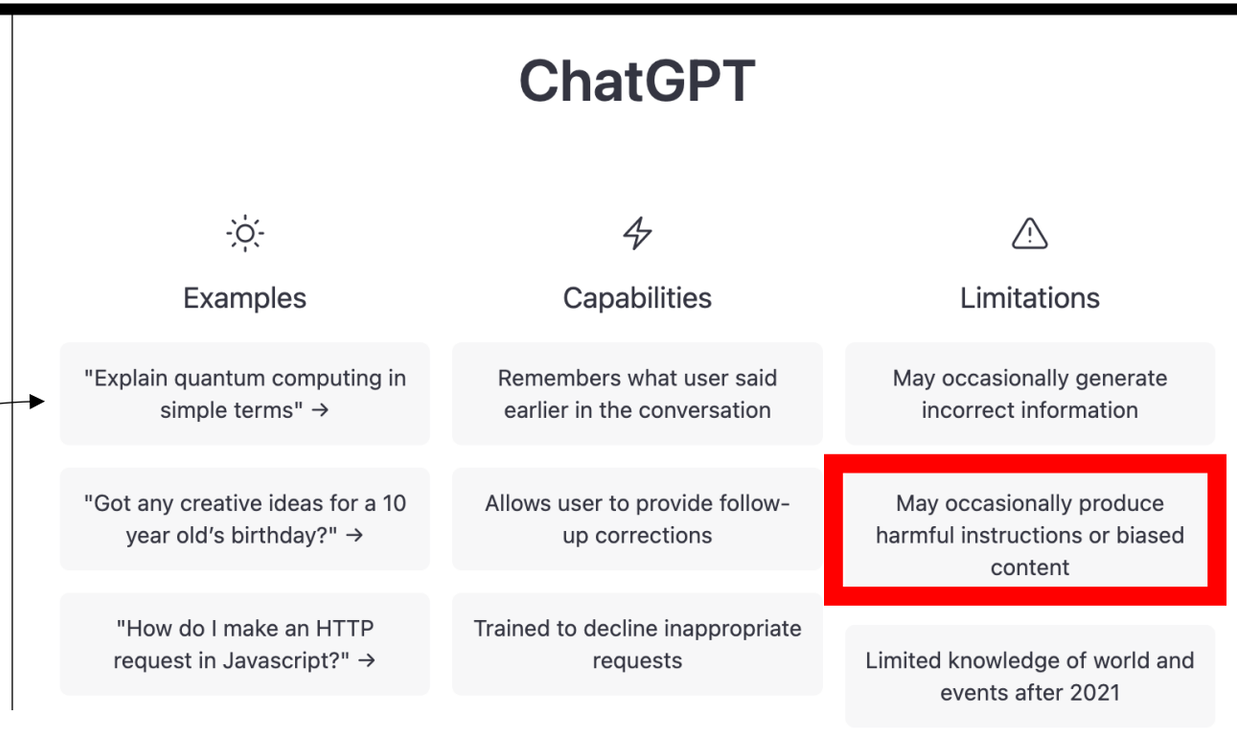
CNN

This AI chatbot is dominating social media with its frighteningly good essays

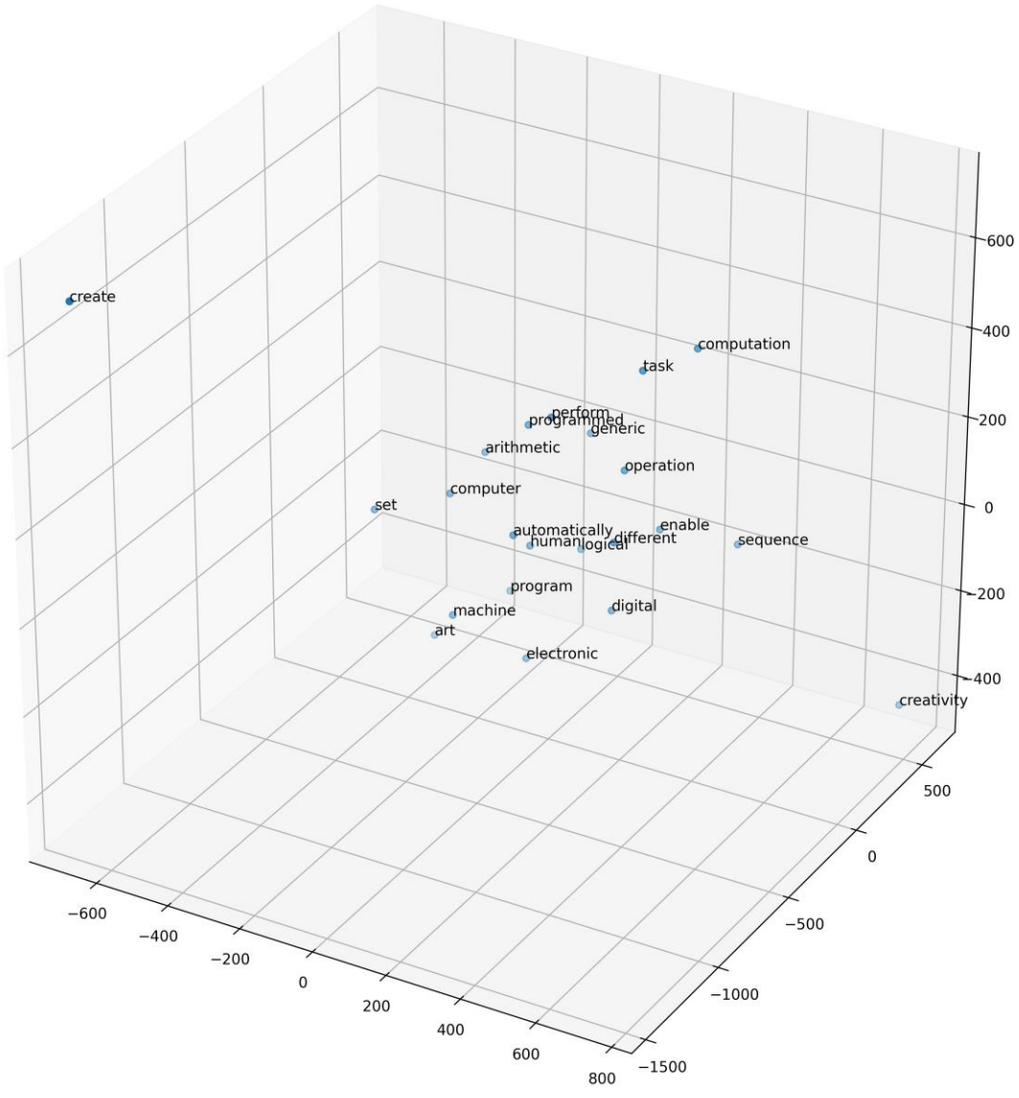
Possible issues. While ChatGPT successfully fielded a variety of questions submitted by CNN, some responses were noticeably off. In fact, Stack...

OpenAI

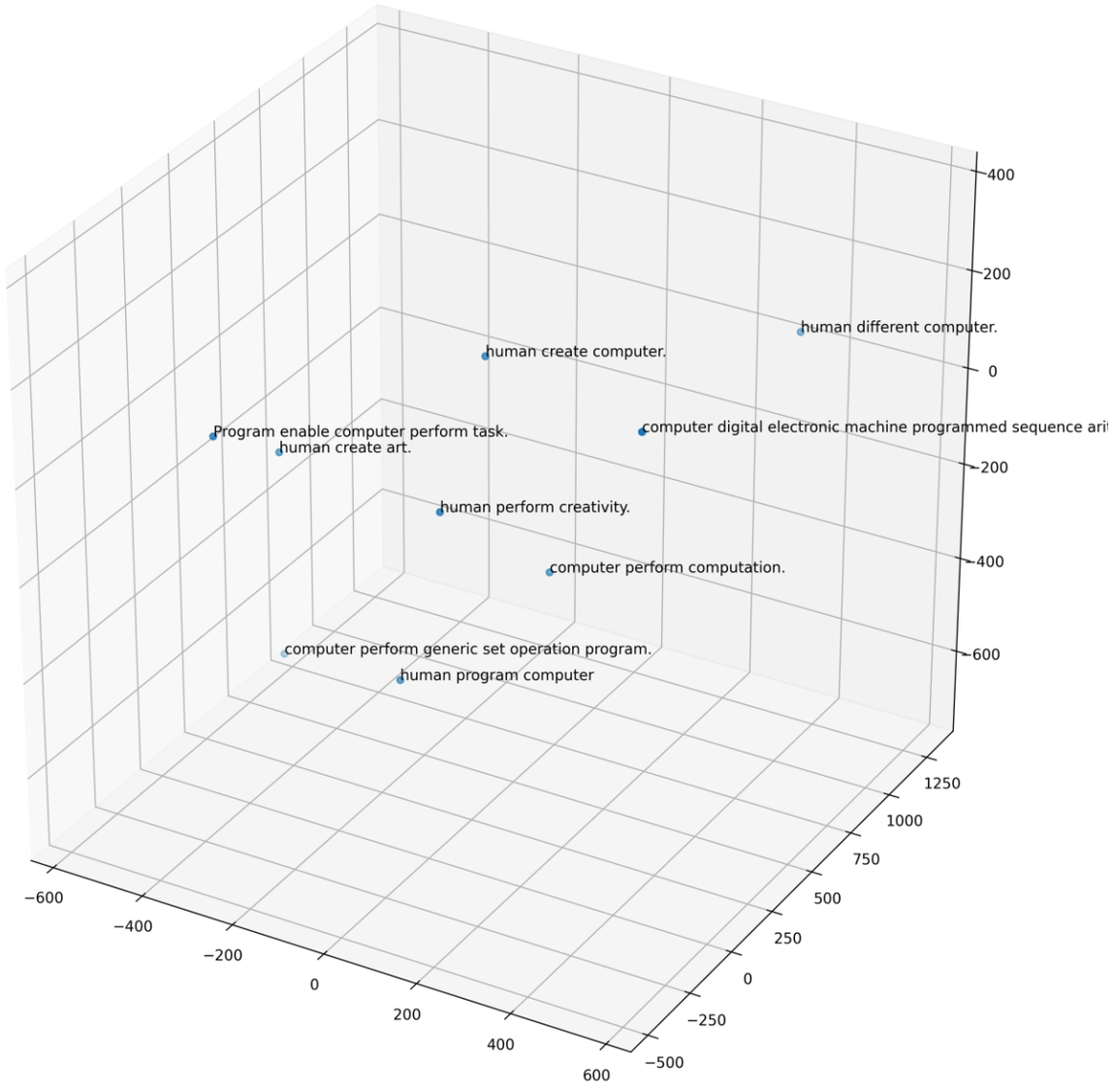
New and Improved Content Moderation Tooling



OpenAI's ChatGPT

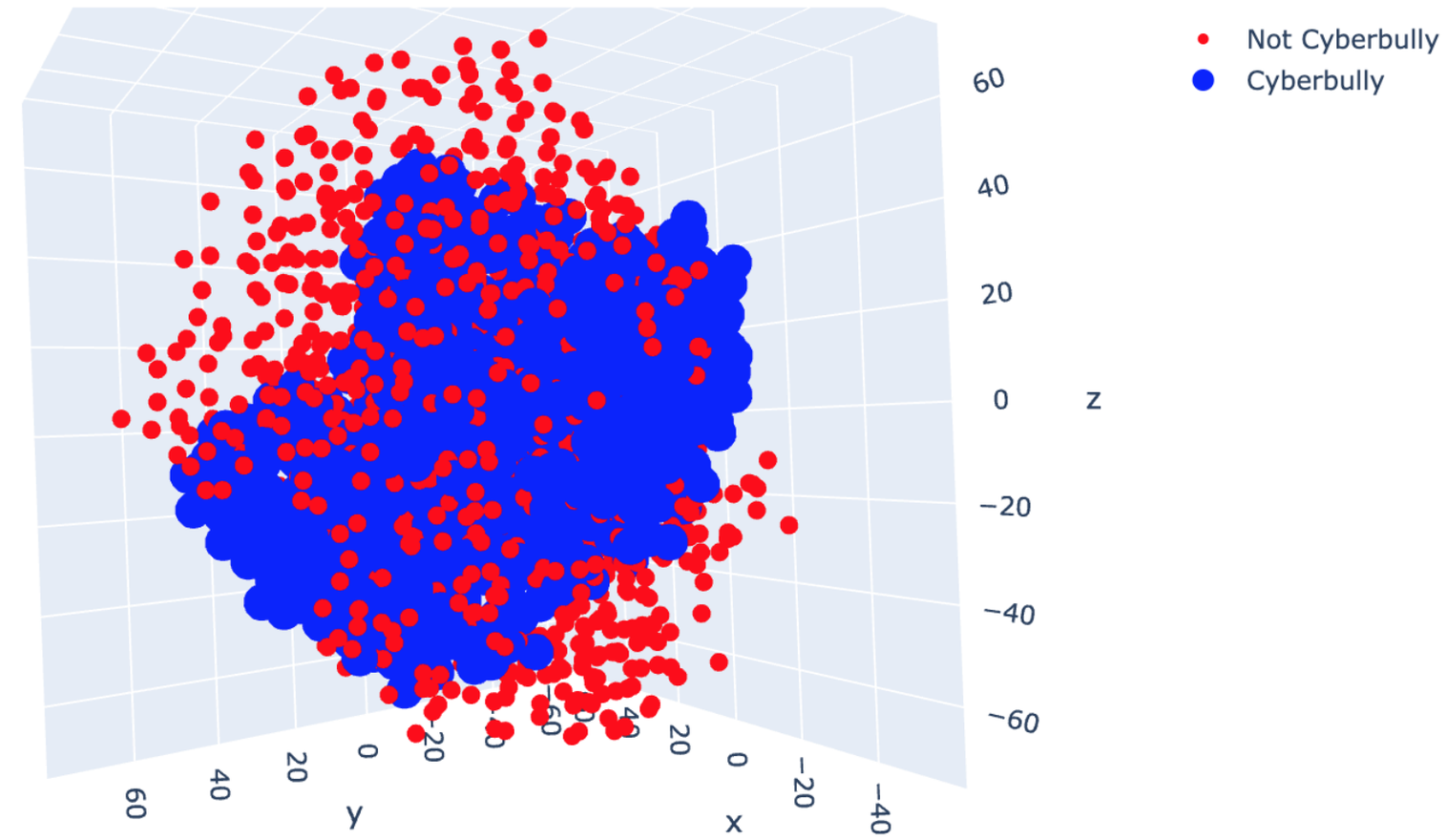


Word Embeddings

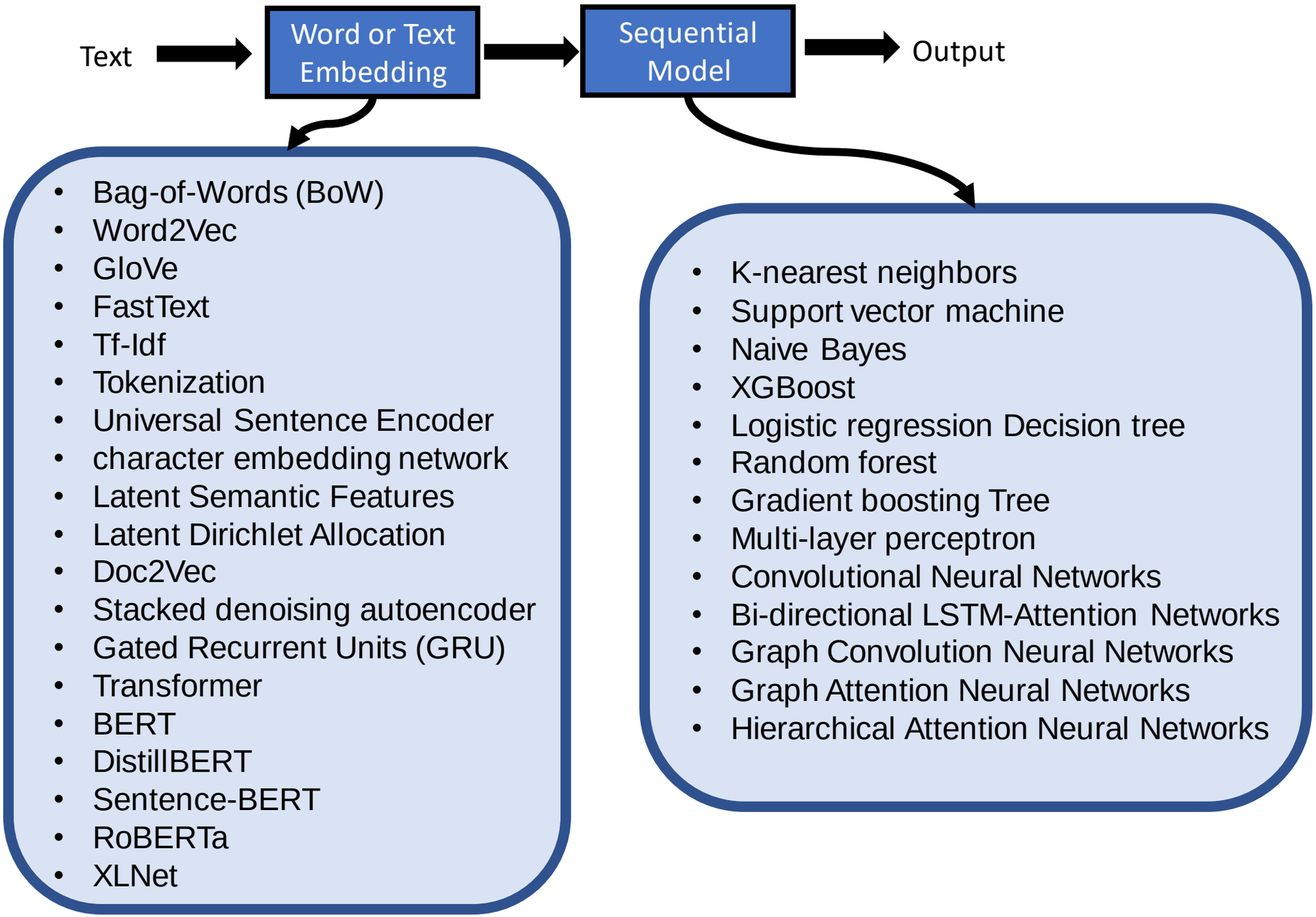


Text Embeddings

Comparison of Word and Textual Embeddings over same data

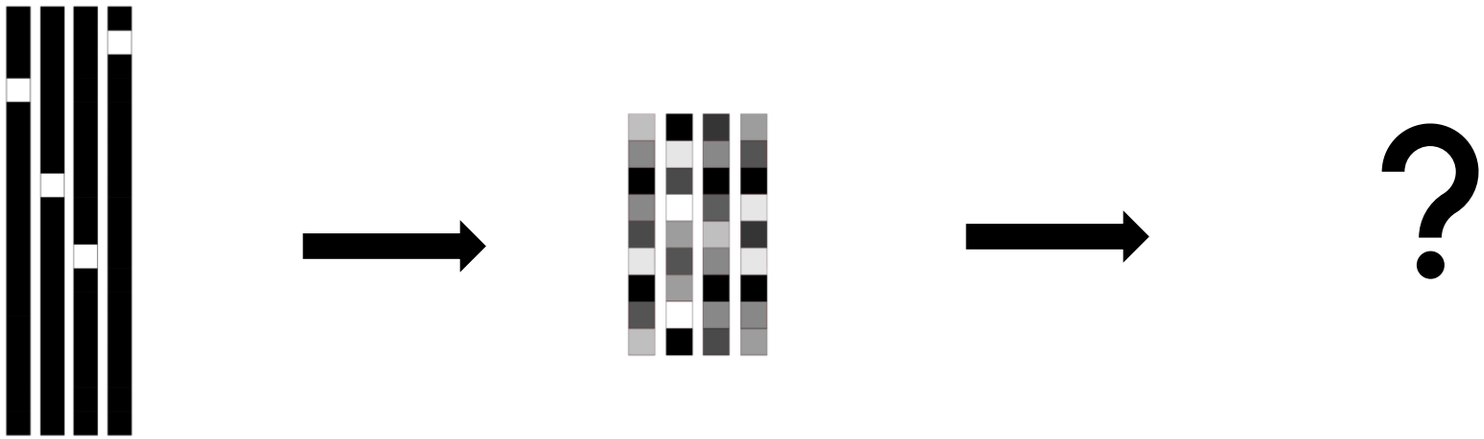


Comparison of Textual Embeddings for Cyerbully and Non-cyberbully related texts



Raw Pipeline of Current Data driven NLP (including Cyberbully Detection)

Research Motivation



<u>One hot coded</u>

- high dimensional
- sparse
- hard coded

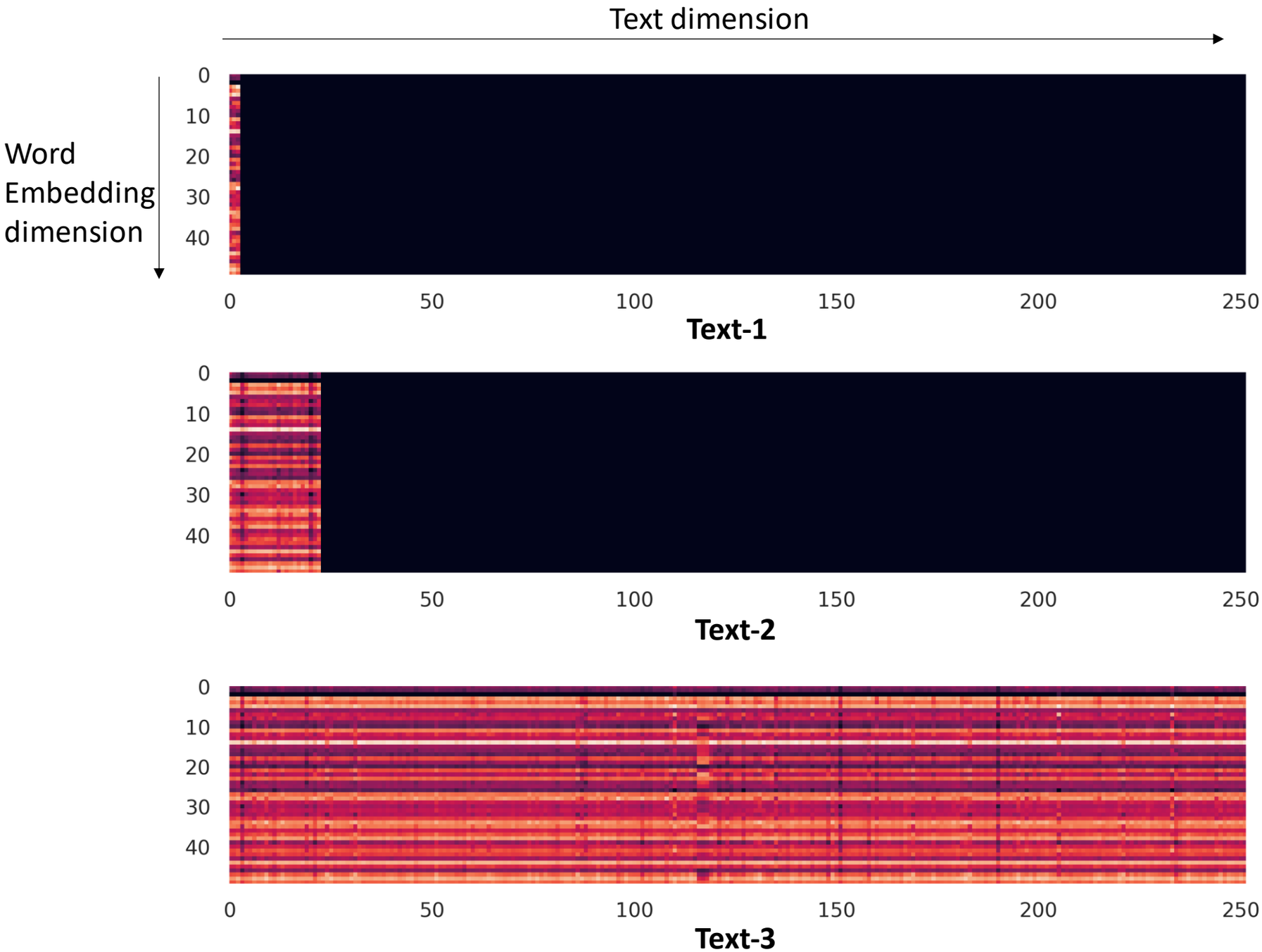
<u>Word2Vec</u>

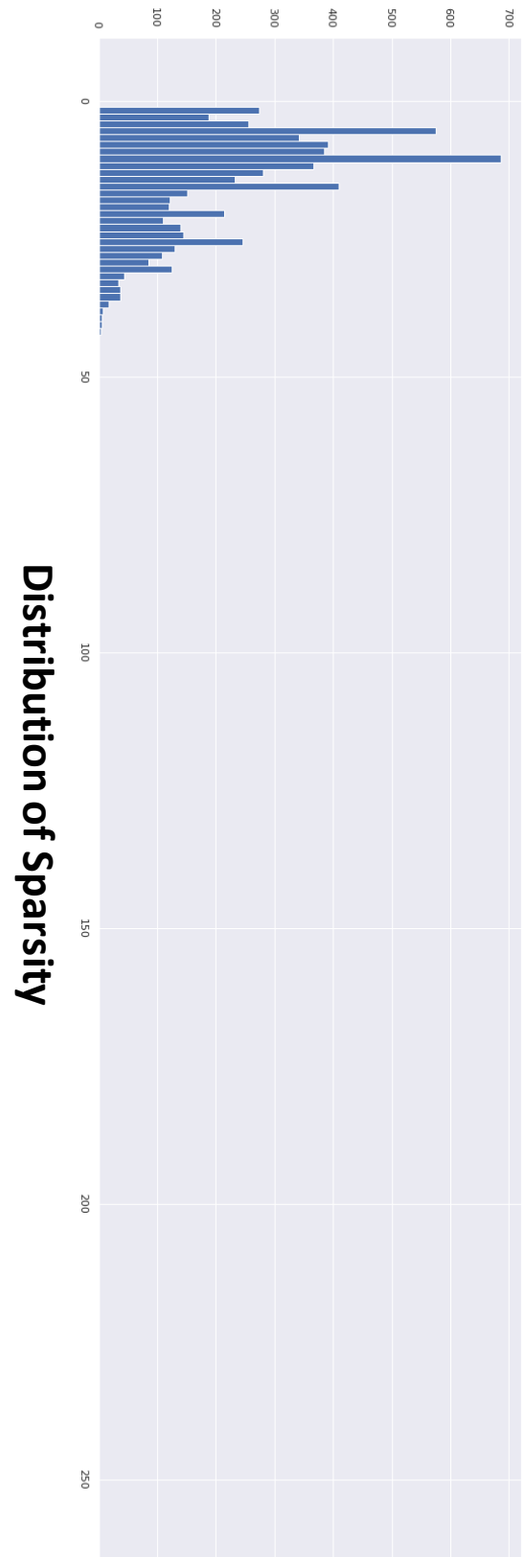
- interpretable in Euclidean space
- low dimensional
- dense (not dense when considered for textual embedding)
- learned from data

<u>Mythical Embedding</u>

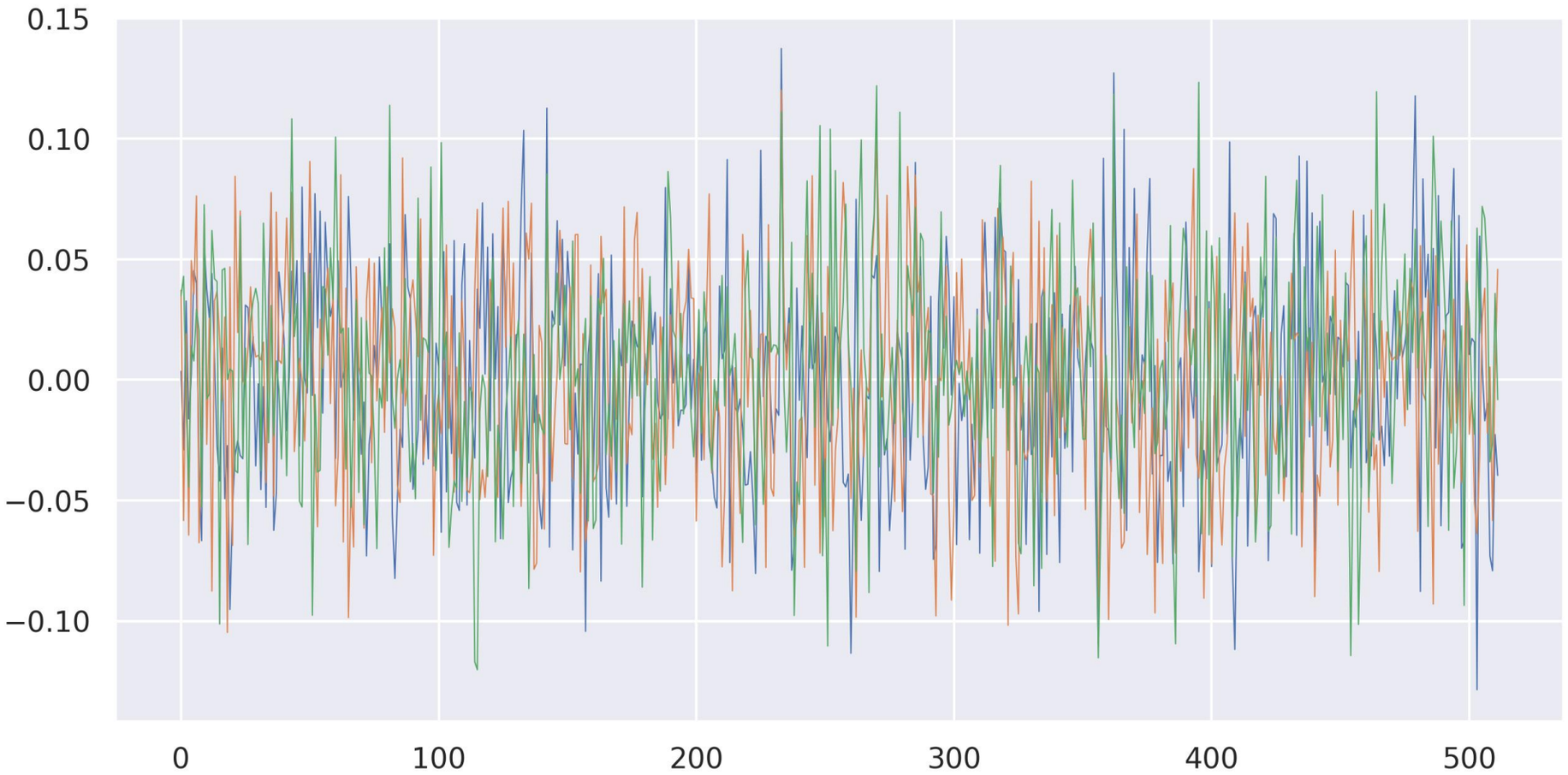
- low dimensional
- interpretable over real domain
- dense in real domain with respect to text
- smooth in real domain with respect to text
- sparse and definite in frequency domain
- learned from data
- invariant to size of text

- **Limitations of State of Art Models**

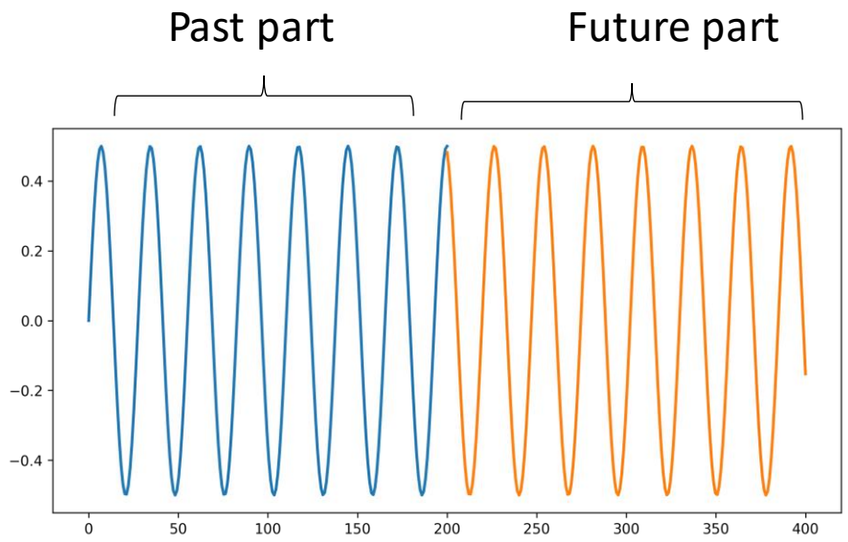


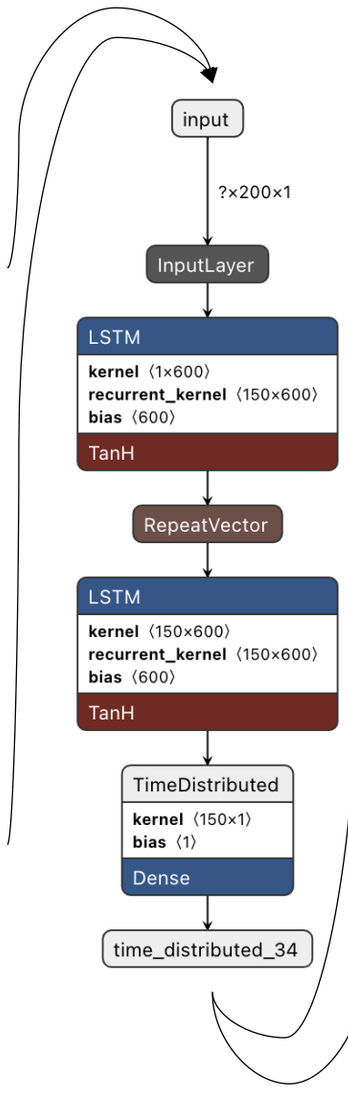


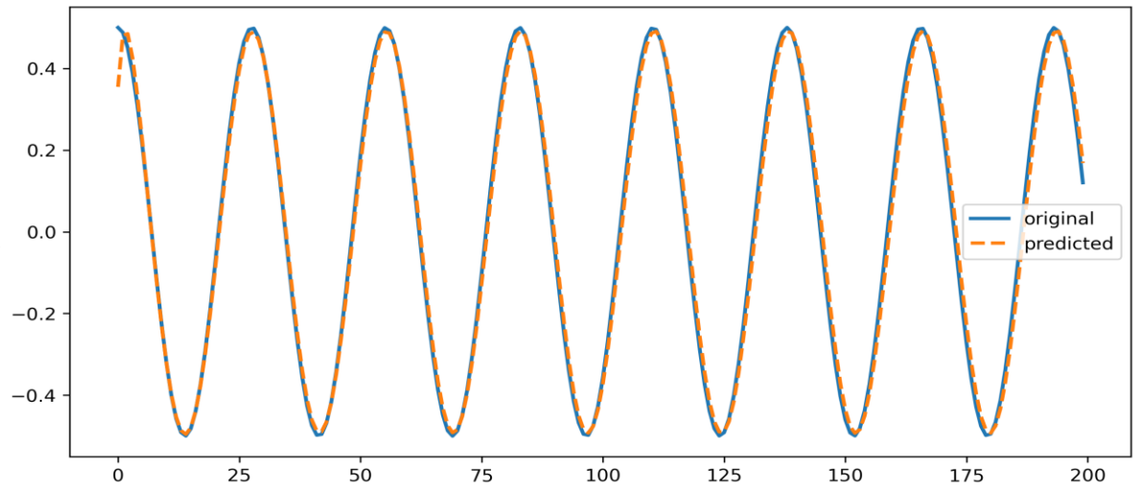
Fallacy of Word Embeddings: Sparsity in sequence format

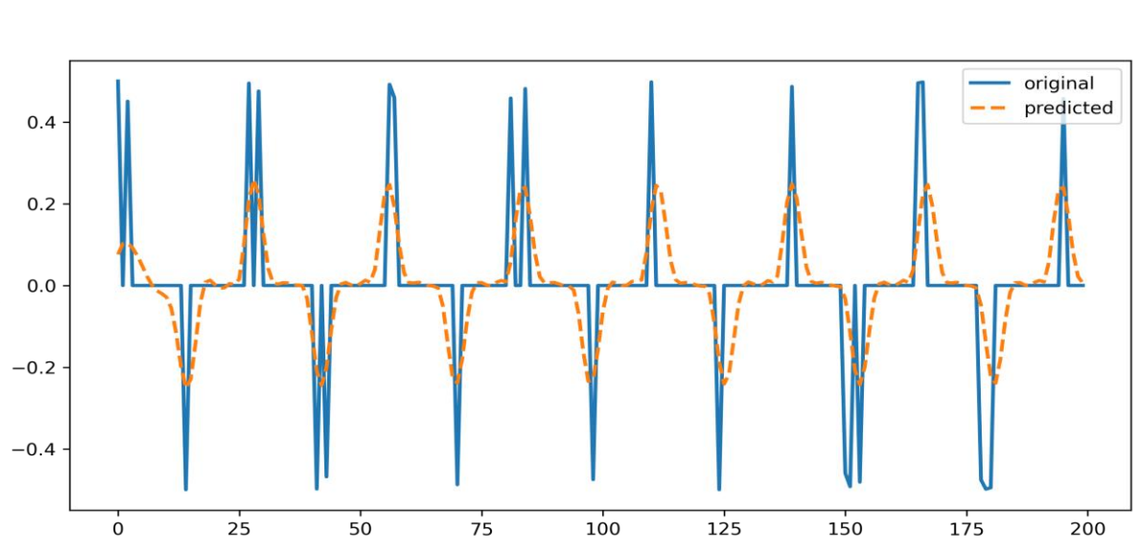


Fallacy of Text Embeddings: Non-smoothness in sequence format

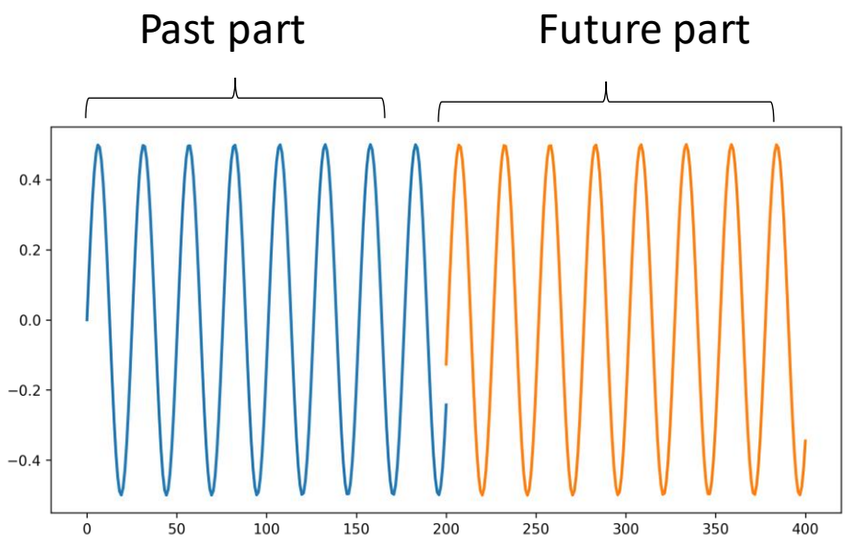


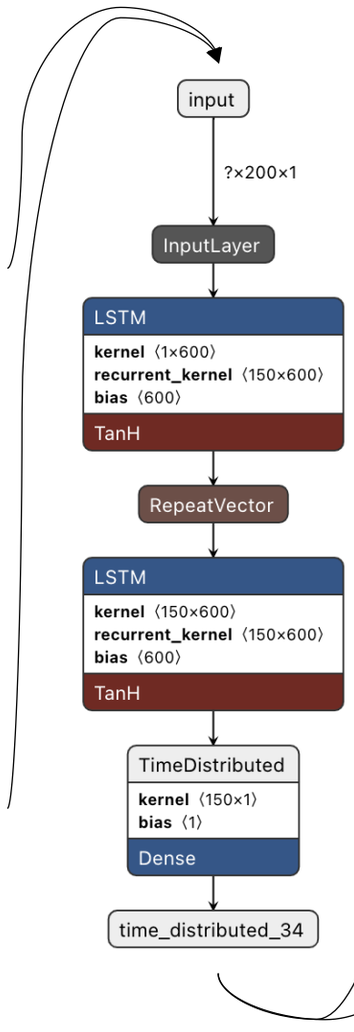


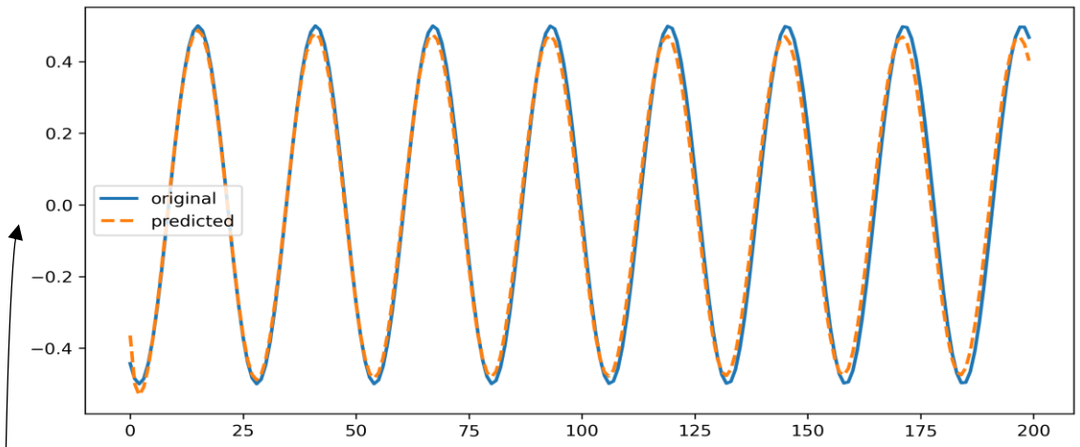


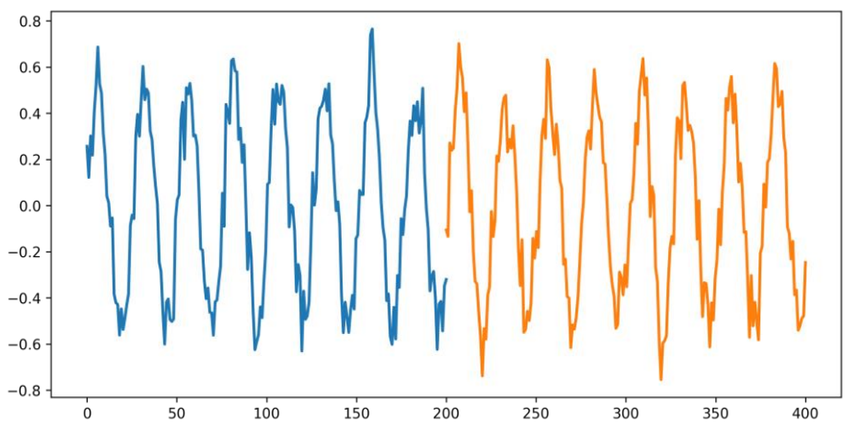


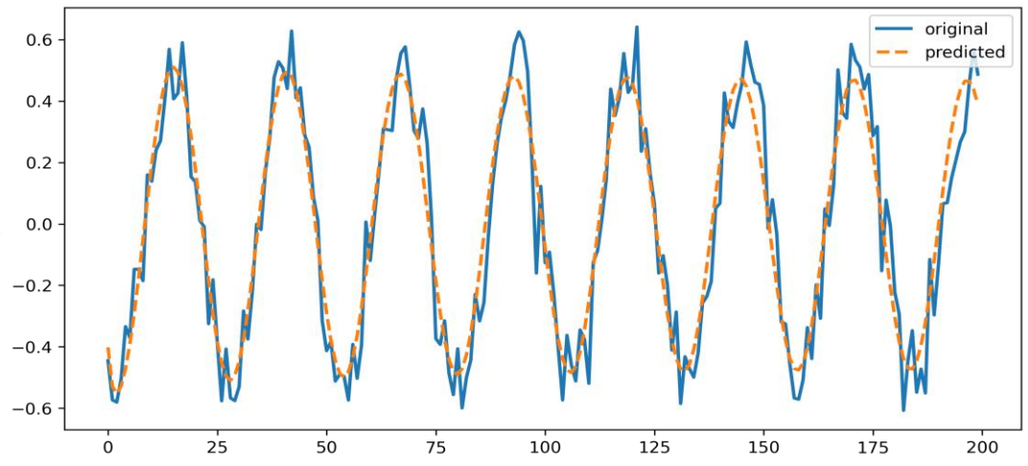
<u>Proposal:</u> Sequential models are not resilient at approximating sparse sequences





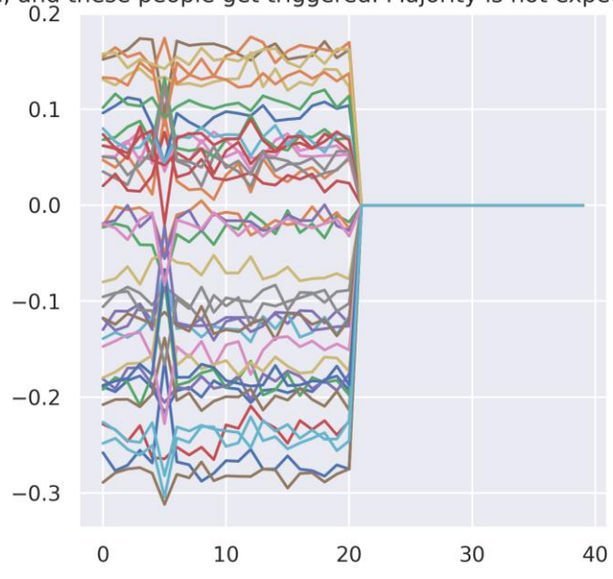




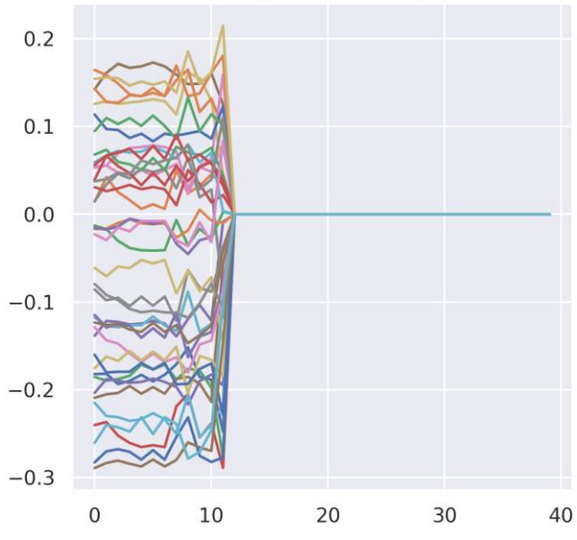


<u>Proposal:</u> Sequential Models are not resillent at approximating non-smooth sequences

Is class shaming justified while condemning rape threats?? Make a gay, trans joke, and these people get triggered. Majority is not expected tolerate the type of shaming that's insulting to minorities just because it's majority.

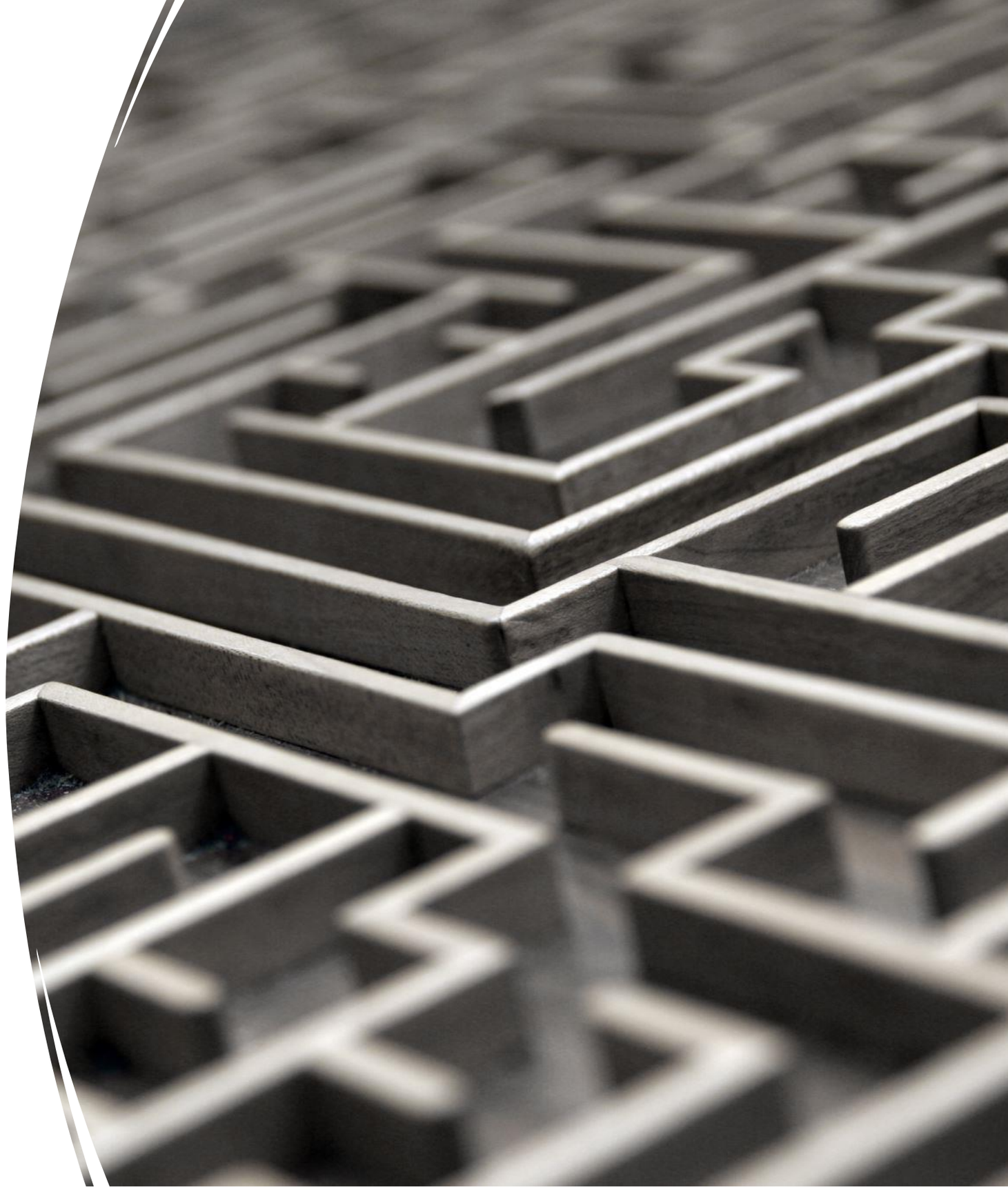


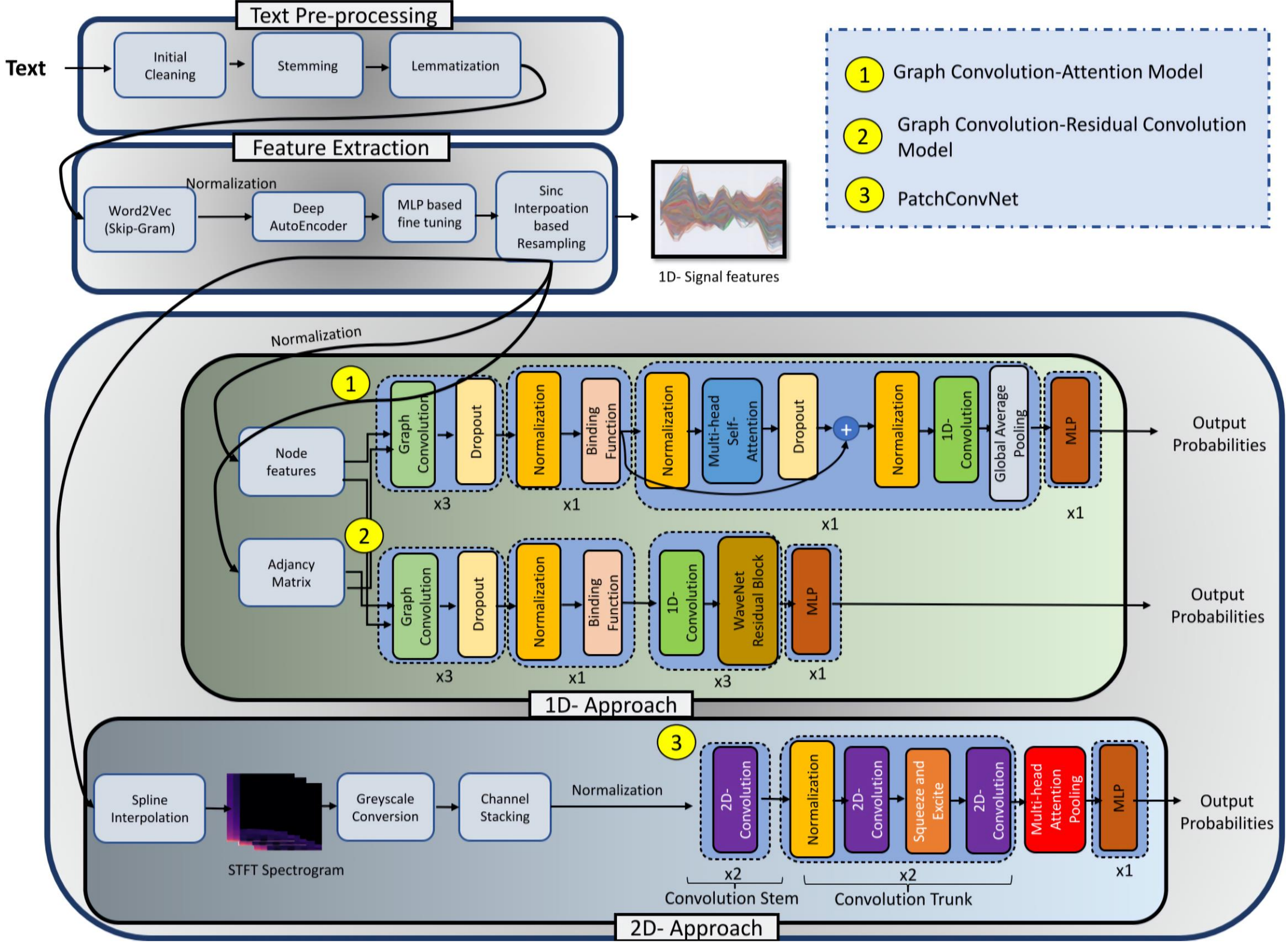
Just heard someone make a "gay" joke and a rape joke within a span of 2 minutes. Very cool... #overheardatUST



<u>Proposal:</u> Lack of uniformness in "window of information" for same context but different length sentences

- **Proposed Approach**





Functional Pipeline

- **Evaluation**

No.	Name	Nature	Classes
1	Fine Grained Cyberbullying Dataset	Single-label, Multi-class	6
2	Toxic Comment Classification Dataset	Multi-label, Multi-class	7

Datasets Considered

Snapshot of Dataset-1

	tweet_text	cyberbullying_type
2	In other words #katandandre, your food was crapilicious! #mkr	not_cyberbullying
3	Why is #aussietv so white? #MKR #theblock #ImACelebrityAU #today #sunrise #studio10 #Neighbours #WonderlandTen #etc	not_cyberbullying
4	@XochitlSuckkks a classy whore? Or more red velvet cupcakes?	not_cyberbullying
5	@Jason_Gio meh. :P thanks for the heads up, but not too concerned about another angry dude on twitter.	not_cyberbullying
6	@RudhoeEnglish This is an ISIS account pretending to be a Kurdish account. Like Islam, it is all lies.	not_cyberbullying
7	@Raja5aab @Quickieleaks Yes, the test of god is that good or bad or indifferent or weird or whatever, it all proves gods existence.	not_cyberbullying
8	Itu sekolah ya bukan tempat bully! Ga jauh kaya neraka	not_cyberbullying
9	Karma. I hope it bites Kat on the butt. She is just nasty. #mkr	not_cyberbullying
10	@stockputout everything but mostly my priest	not_cyberbullying

Snapshot of Dataset-2

comment_text	toxic	severe_toxic	obscene	threat	insult	identity_hate
Explanation	0	0	0	0	0	0
D'aww! He matches this background colour I'm seemingly stuck with. Thanks. (talk) 21:51, Januar	0	0	0	0	0	0
Hey man, I'm really not trying to edit war. It's just that this guy is constantly removing relevant inf	0	0	0	0	0	0
"	0	0	0	0	0	0
You, sir, are my hero. Any chance you remember what page that's on?	0	0	0	0	0	0
"	0	0	0	0	0	0
COCKSUCKER BEFORE YOU PISS AROUND ON MY WORK	1	1	1	0	1	0
Your vandalism to the Matt Shirvington article has been reverted. Please don't do it again, or you	0	0	0	0	0	0
Sorry if the word 'nonsense' was offensive to you. Anyway, I'm not intending to write anything in t	0	0	0	0	0	0
alignment on this subject and which are contrary to those of DuLithgow	0	0	0	0	0	0
"	0	0	0	0	0	0

Single label

Multi label

Precision: measure of the accuracy of the classifier when it predicts the positive class. High precision means that the model is good at identifying positive examples and minimizing false positives

Recall: measure of the classifier's ability to correctly identify the positive class. High recall means that the model is good at identifying all of the positive examples in the data and minimizing false negatives

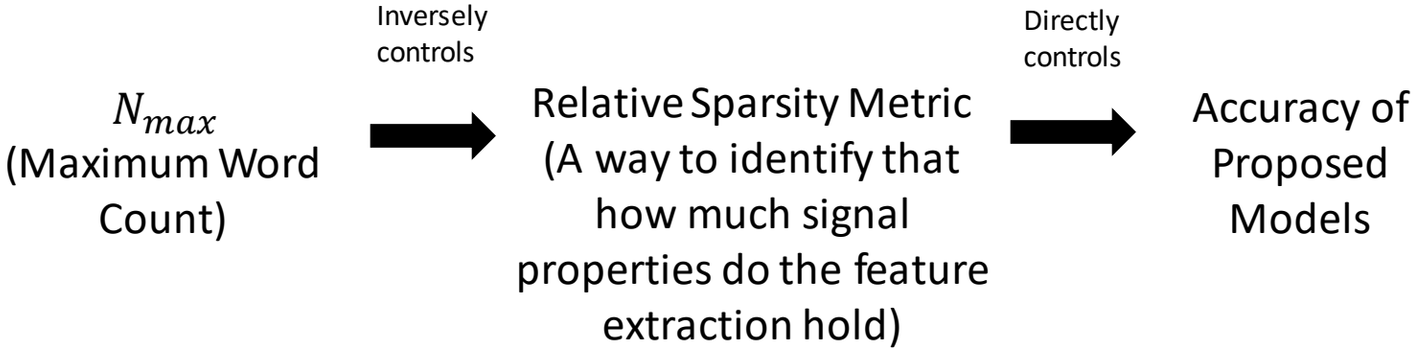
F_1 score: harmonic mean of precision and recall, and is a good metric to use when you want to balance precision and recall

Accuracy: ratio of predictions that are correct

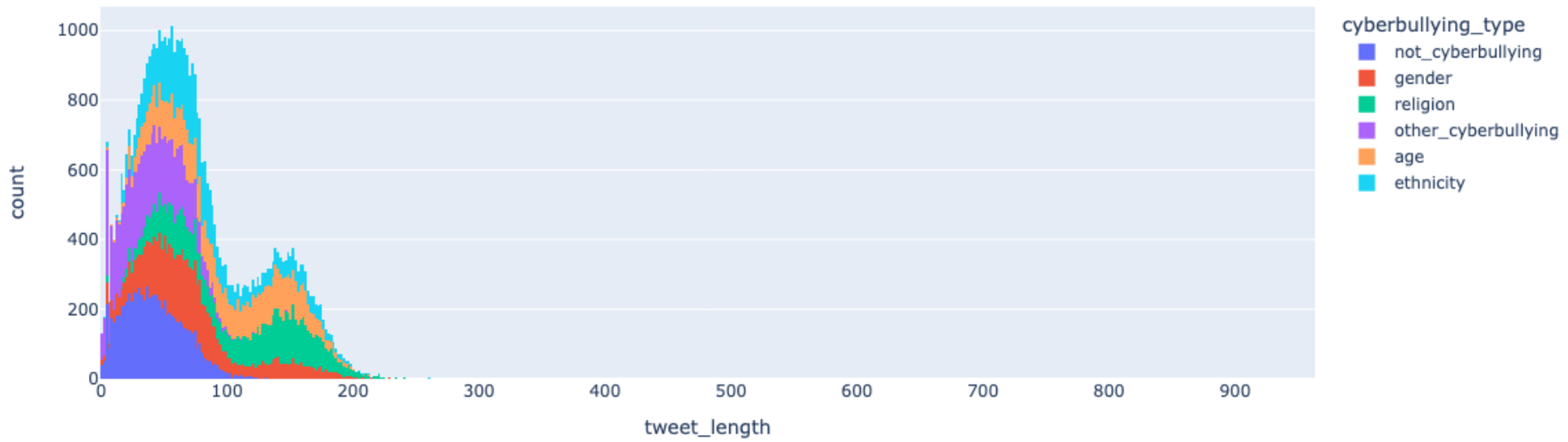
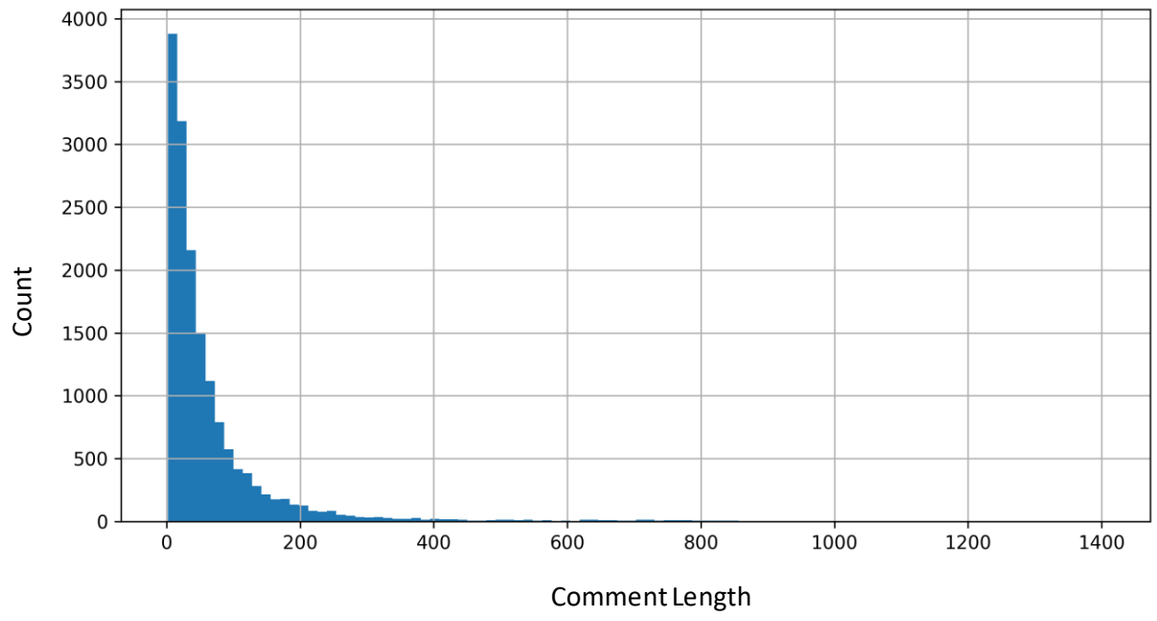
Hamming Loss: A measure of the number of incorrect predictions made by a classifier. It is the fraction of the wrong labels to the total number of labels.

Total parameters: sum of trainable parameters (TP) and pretrained parameters (PP), which inversely accounts for inference time of deep learning models.

Performance Metrics



Main Hypothesis of Proposed Scheme

Dataset-1	
Dataset-2	

Word Count per Text Distribution

ID	Description	TP	PP	LR	Epochs
M_1	BERT-MLP	$5.26\text{x}10^5$	$1.09\text{x}10^8$	0.001	50
M_2	DistillBERT-MLP	$5.26\text{x}10^5$	$6.68\text{x}10^7$	0.001	50
M_3	SentenceBERT-GCN	$1.35\text{x}10^4$	$2.25\text{x}10^7$	0.001	50
M_4	SentenceBERT-GAN	$8.31\text{x}10^6$	$2.25\text{x}10^7$	0.001	50
M_5	GCN-Attention (1D)	$1.38\text{x}10^5$	0	0.001	50
M_6	GCN-Residual (1D)	$2.31\text{x}10^6$	0	0.001	50
M_7	PatchConvnet (2D)	$1.38\text{x}10^6$	0	0.001	50

Proposed models have 10 to 1000 times less total parameter count than benchmark models

Evaluation Models with trainable parameter (TP) and pretrained parameter (PP)

TP: Trainable Parameters, PP: Pretrained Parameters, LR: Learning Rate

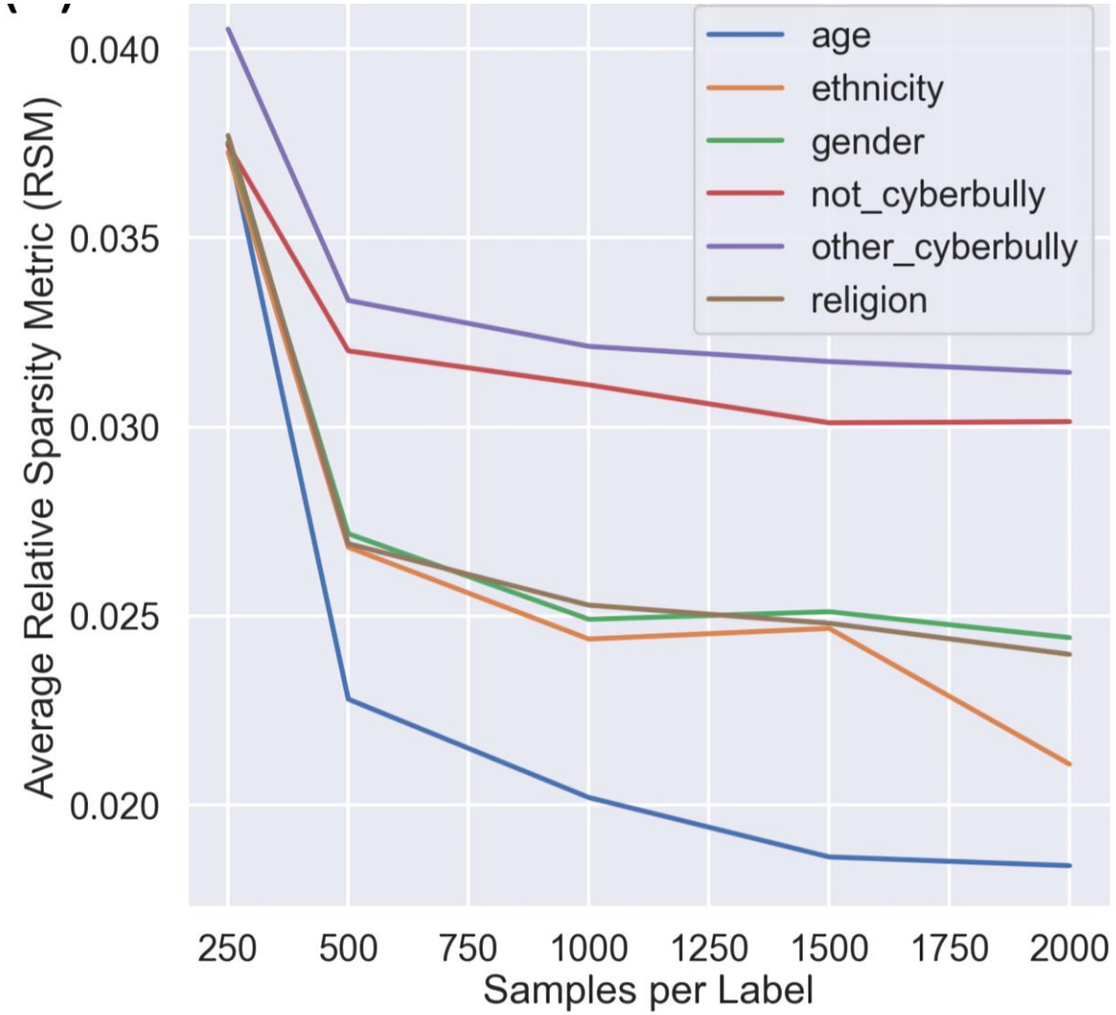
Metric	M_1	M_2	M_3	M_4	M_5	M_6	M_7
250 samples per label (N_{max} = 40)							
A	70.95	72.97	66.67	73.66	76.35	74.66	57.72
P	72.85	78.96	65.67	72.92	76.95	74.91	57.99
R	70.55	73.34	66.89	74.15	75.2	73.51	58.23
F	71.18	70.64	64.28	73.24	75.3	73.83	56.74
500 samples per label (N_{max}= 144)							
A	73.46	73.46	68.8	76.24	83.80	83.08	68.16
P	72.74	76.22	71.5	75.39	84.17	83.52	66.31
R	73.76	72.06	69.91	75.57	84.29	83.58	66.15
F	72.92	72.10	69.97	75.42	84.87	83.43	64.41
1000 samples per label (N_{max} = 252)							
A	71.97	73.41	64.21	75.82	85.41	84.22	82.01
P	75.04	73.30	65.16	76.00	85.14	85.11	86.22
R	72.16	72.47	65.74	75.91	85.15	84.24	81.71
F	71.05	72.28	64.91	75.78	84.46	84.25	82.01
1500 samples per label (N_{max} = 252)							
A	72.94	68.76	67.47	79.14	88.30	87.36	88.82
P	74.29	69.62	66.41	79.75	88.05	87.17	88.95
R	73.78	68.09	66.81	79.46	88.38	87.45	88.85
F	73.18	67.92	65.02	79.57	88.15	87.28	88.47
2000 samples per label (N_{max} = 252)							
A	72.63	73.49	70.19	77.82	87.42	86.37	87.96
P	72.84	74.5	71.69	77.71	87.46	86.18	88.08
R	73.05	74.42	70.39	77.75	87.39	86.38	87.79
F	72.60	74.56	69.55	77.64	87.52	86.18	87.73

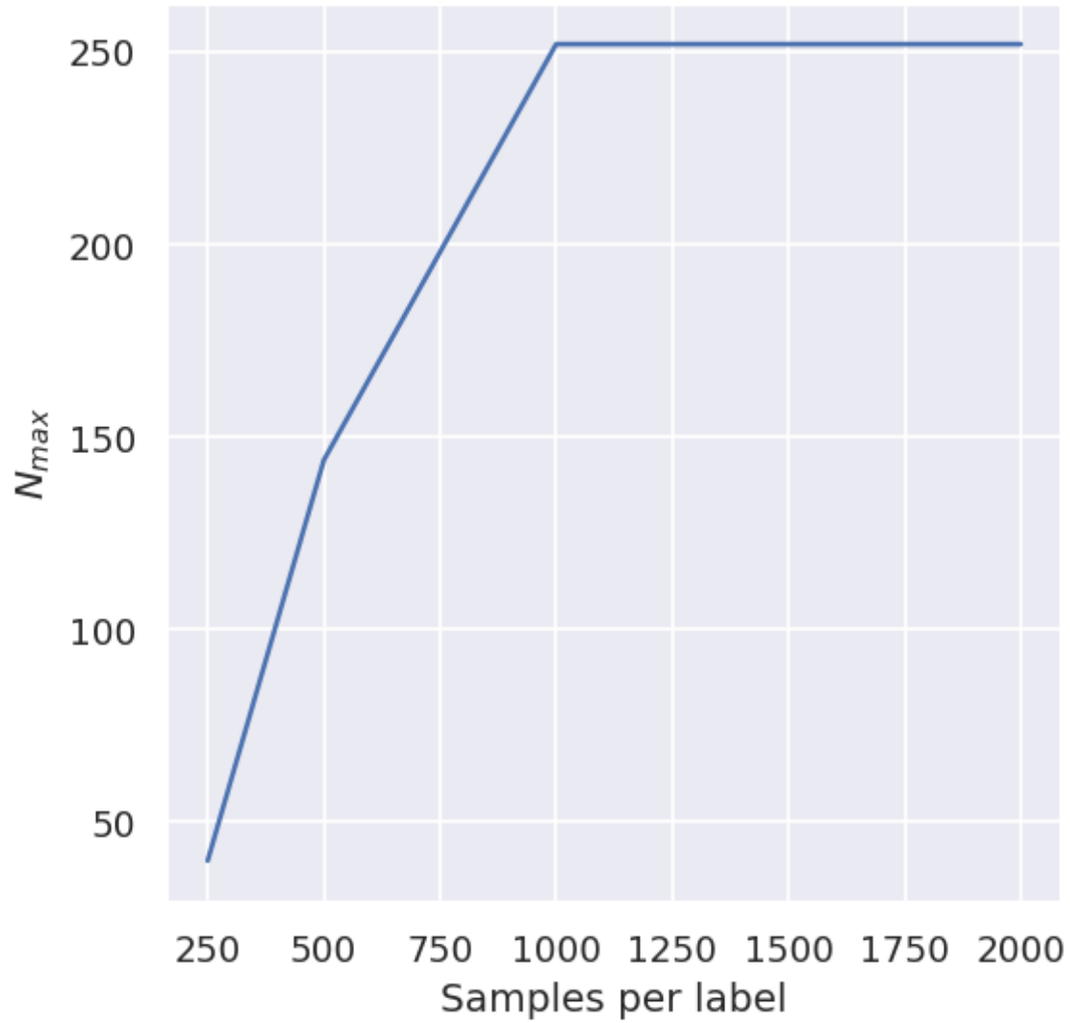
Dataset-1 evaluation (scores)

Models	H	P	R	F	A
2000 Samples (N_{max} = 797)					
M_1	0.0675	0.8218	0.8472	0.8282	0.8078
M_2	0.0534	0.853	0.8587	0.8533	0.8177
M_3	0.0802	0.7988	0.8054	0.7981	0.7832
M_4	0.0679	0.818	0.8806	0.8333	0.7851
M_5	0.0953	0.8004	0.8004	0.8004	0.8005
M_6	0.0891	0.8122	0.8322	0.8128	0.8208
M_7	0.0879	0.8226	0.8226	0.8226	0.8226
4000 Samples (N_{max} = 834)					
M_1	0.0431	0.8781	0.9034	0.8841	0.8659
M_2	0.0398	0.8950	0.9102	0.9003	0.8686
M_3	0.0798	0.8071	0.8049	0.7989	0.7908
M_4	0.0494	0.8668	0.9056	0.8764	0.8455
M_5	0.0337	0.9262	0.9305	0.9244	0.8726
M_6	0.0360	0.9341	0.9320	0.9262	0.8512
M_7	0.0459	0.8940	0.9101	0.8976	0.8659

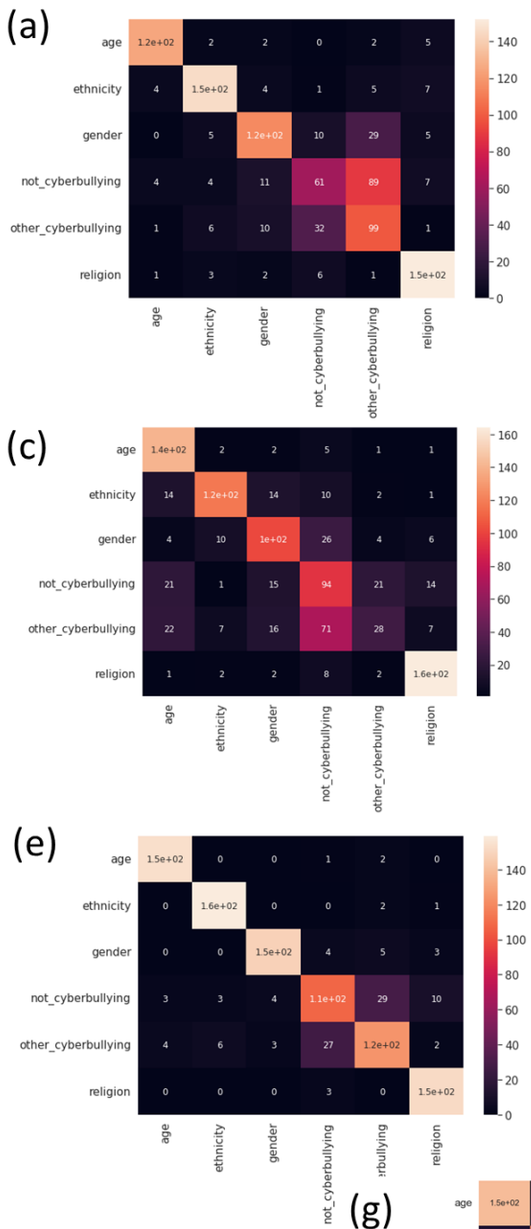
Dataset-2 evaluation (percentages)

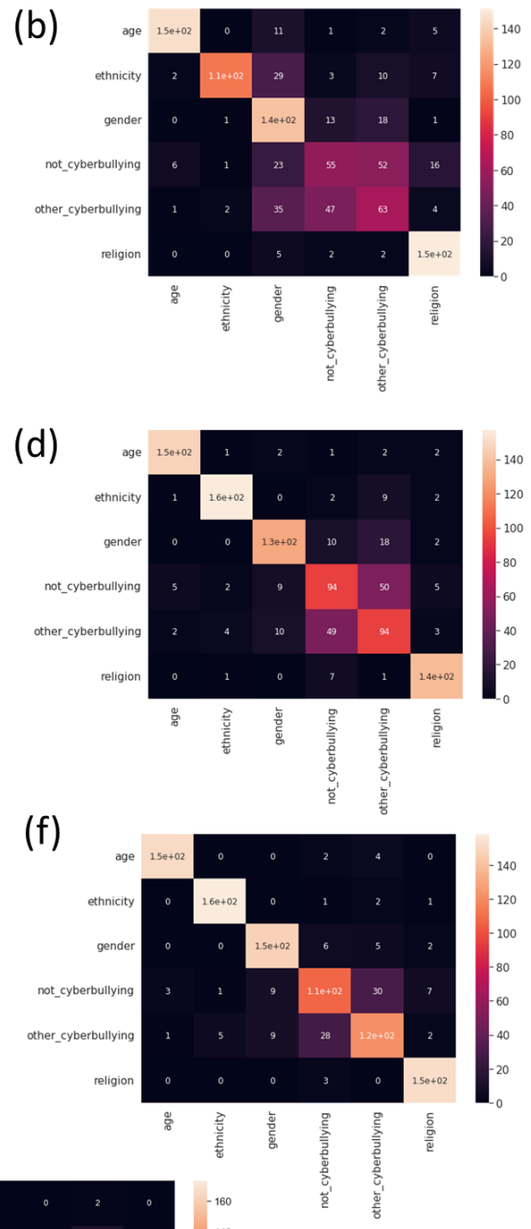
A: Accuracy
P: Precision
R: Recall
F: F_1 score
H: Hamming Loss

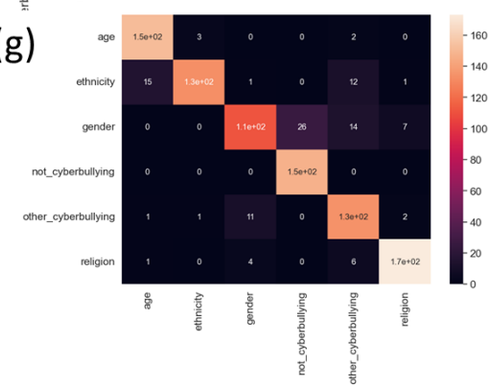




Relationship between N_{max} and Relative Sparsity Metric







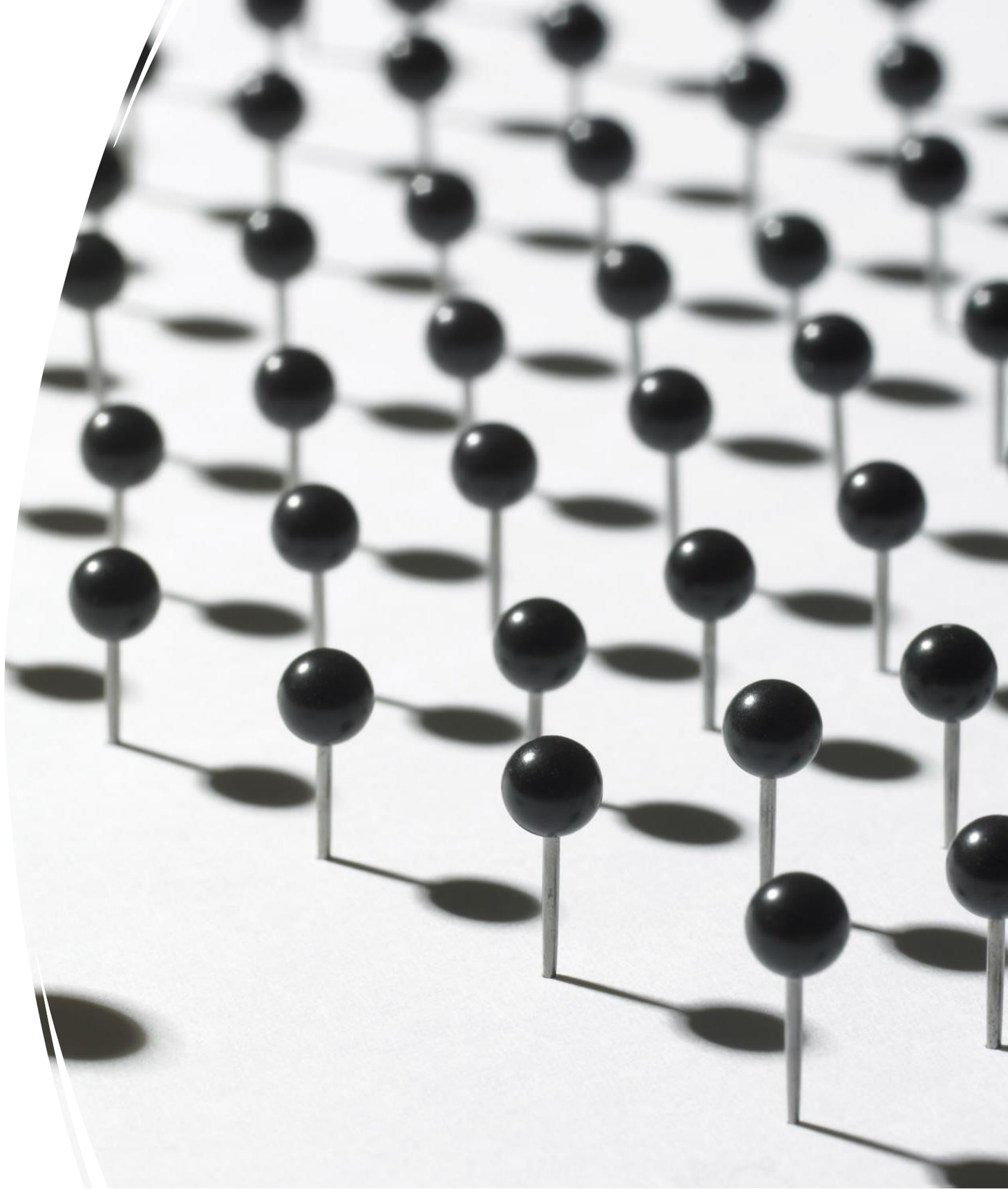
(a) BERT-MLP
(b) DistillBERT-MLP
(c) SBERT-GCN
(d) SBERT-GAN
(e) GCN-Attention *
(f) GCN-Residual *
(g) PatchConvNet *

Classification Confusion Matrices (Dataset-1)

- **Conclusion**

- I illuminated on **some fallacies** of the **state of the art models**
- Leveraging this, I proposed a novel **“signal feature”** extraction scheme
- I further developed **three new deep learning models** for cyberbully classification
- I **evaluated** my proposed approaches over different datasets, as well as different benchmark models
- I showed that proposed approaches have greater accuracy scores with advantage of lesser parameter count

- **References**



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