GEO AI
LMR CHALLENGE

By: Team GateID

Members:

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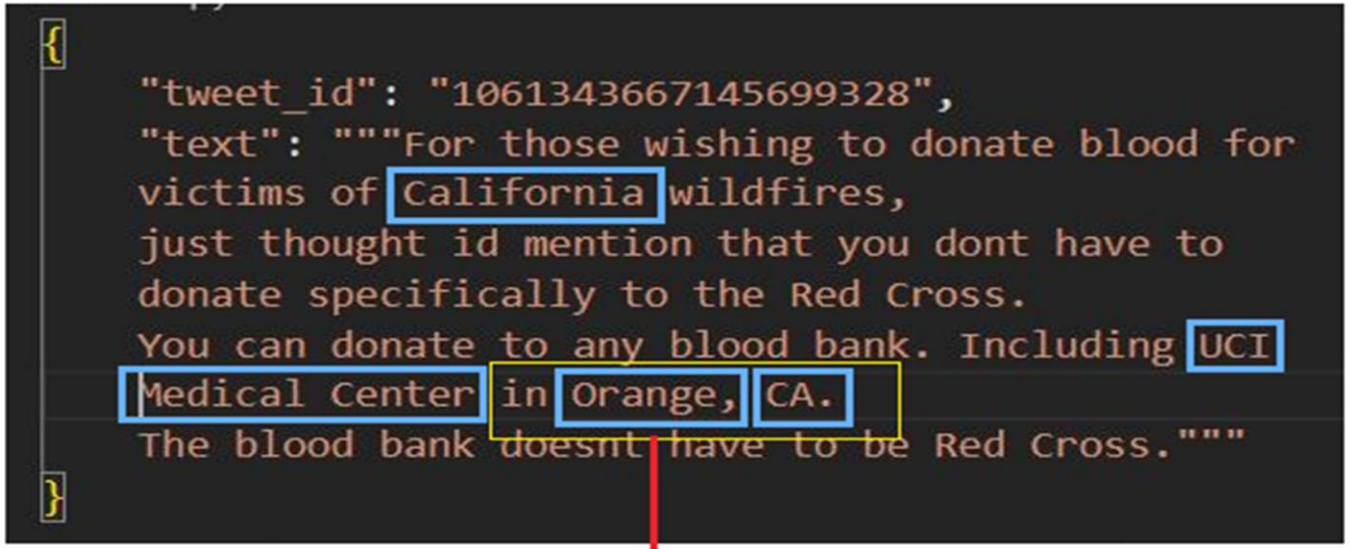
Motivation

Assumption


{
"tweet_id": "1061343667145699328",
"text": """For those wishing to donate blood for
victims of California wildfires,
just thought id mention that you dont have to
donate specifically to the Red Cross.
You can donate to any blood bank. Including UCI
Medical Center in Orange, CA.
The blood bank doesnt have to be Red Cross."""
}
Relationship signify with previous words that its a place.

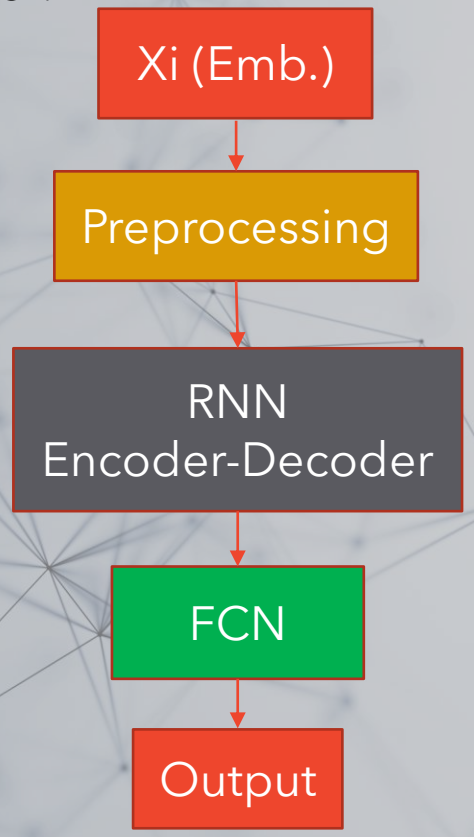
Challenges

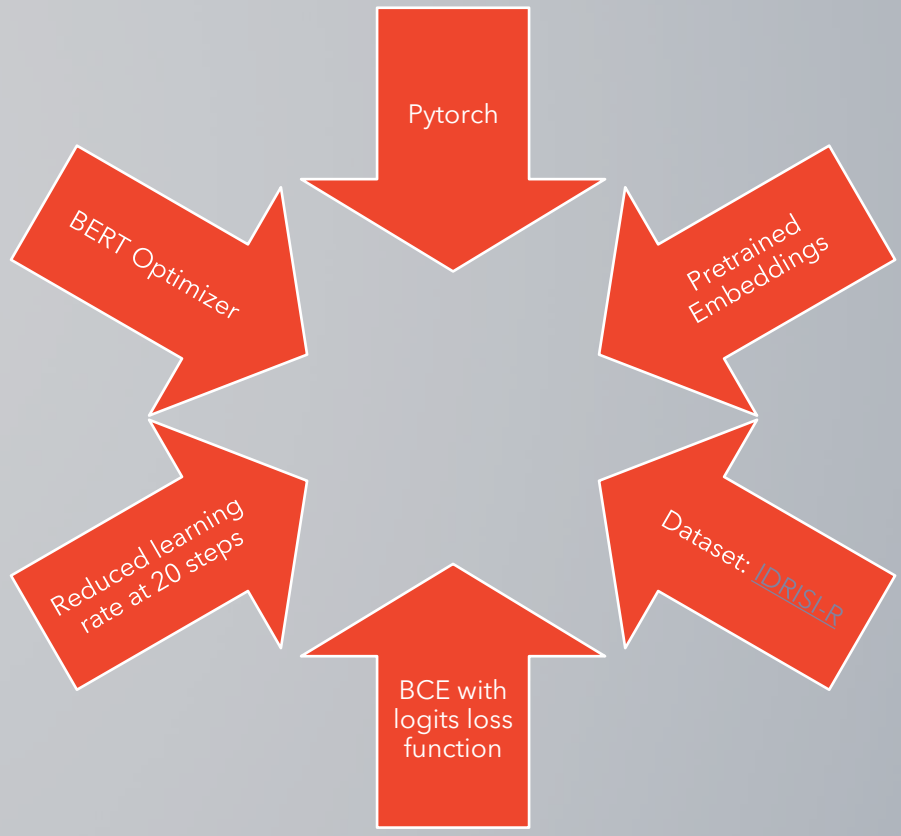
- Insufficient Data
- Variation in benchmark dataset
- Structure of sentence (Non-uniformity)
- Un-balanced Data

[w1	w2	w3	w4	w5	w6	w7	w8	w9]
[1	0	1	0	0	0	0	0	0]

Methodology

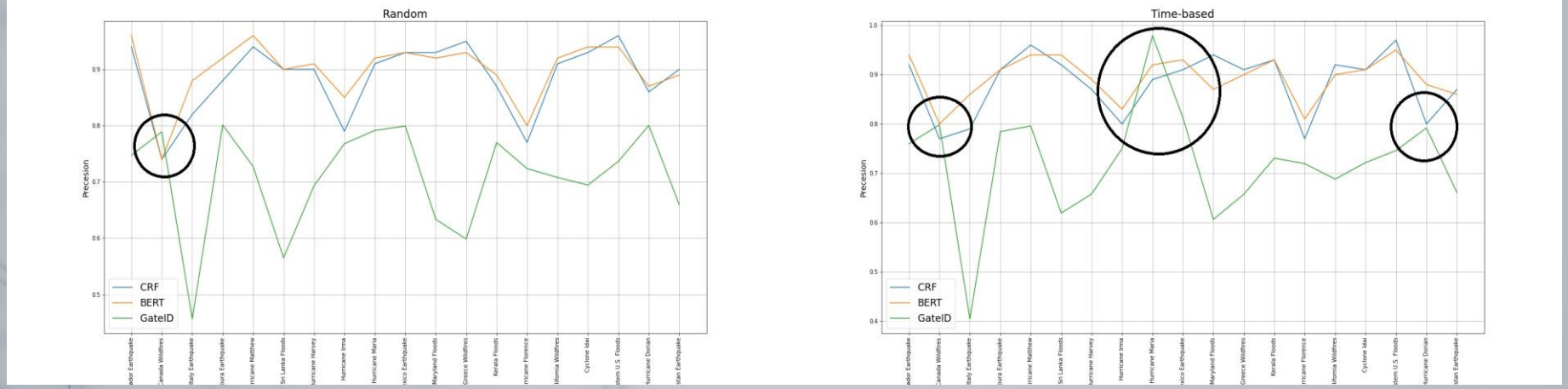
- Proposed Model:





Results

	Random												Time-based											
	CRF			BERT			GPNE			GateID			CRF			BERT			GPNE			GateID		
Event	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
Ecuador Earthquake	0.94	0.91	0.92	0.96	0.95	0.95	0.27	0.23	0.24	0.74728	0.44159	**0.55411**	0.92	0.89	0.9	0.94	0.93	0.93	0.16	0.16	0.16	0.75983	0.45667	**0.56963**
Canada Wildfires	0.74	0.75	0.73	0.74	0.76	0.74	0.43	0.46	0.44	0.78911	0.55785	**0.65143**	0.77	0.75	0.75	0.8	0.8	0.79	0.09	0.1	0.09	0.79845	0.53005	**0.62904**
Italy Earthquake	0.82	0.81	0.82	0.88	0.88	0.87	0.73	0.74	**0.73**	0.45652	0.26923	0.33871	0.79	0.77	0.78	0.86	0.86	0.85	0.36	0.36	**0.36**	0.40476	0.24286	0.30357
Kaikoura Earthquake	0.88	0.87	0.87	0.92	0.92	0.91	0.6	0.6	0.59	0.80129	0.61218	**0.69264**	0.91	0.88	0.88	0.91	0.89	0.89	0.17	0.17	0.17	0.78459	0.57514	**0.66271**
Hurricane Matthew	0.94	0.89	0.9	0.96	0.94	0.94	0.15	0.14	0.14	0.72733	0.41948	**0.53126**	0.96	0.92	0.93	0.94	0.96	0.94	0.04	0.04	0.04	0.79605	0.47507	**0.59352**
Sri Lanka Floods	0.9	0.85	0.87	0.9	0.9	0.89	0.43	0.45	0.42	0.5652	0.40286	**0.47035**	0.92	0.88	0.89	0.94	0.94	0.94	0.2	0.26	0.21	0.61946	0.44132	**0.51542**
Hurricane Harvey	0.9	0.88	0.89	0.91	0.9	0.9	0.36	0.47	0.4	0.69318	0.39103	**0.49816**	0.87	0.86	0.87	0.89	0.89	0.89	0.11	0.11	0.11	0.65821	0.31969	**0.4274**
Hurricane Irma	0.79	0.78	0.78	0.85	0.85	0.84	0.34	0.45	0.37	0.768	0.45886	**0.57375**	0.8	0.79	0.79	0.83	0.83	0.82	0.11	0.11	0.11	0.75019	0.4215	**0.5395**
Hurricane Maria	0.91	0.88	0.88	0.92	0.91	0.91	0.45	0.56	0.48	0.79159	0.61257	**0.68869**	0.89	0.85	0.86	0.92	0.94	0.92	0.19	0.22	0.19	0.9791	0.66217	**0.78717**
Mexico Earthquake	0.93	0.91	0.92	0.93	0.93	0.93	0.79	0.8	**0.78**	0.79933	0.50541	0.6179	0.91	0.87	0.88	0.93	0.92	0.92	0.35	0.34	0.34	0.81239	0.49363	**0.61335**
Maryland Floods	0.93	0.89	0.9	0.92	0.9	0.9	0.74	0.8	**0.75**	0.63346	0.46032	0.53319	0.94	0.79	0.83	0.87	0.81	0.82	0.45	0.47	0.43	0.60662	0.40507	**0.48501**
Greece Wildfires	0.95	0.93	0.93	0.93	0.93	0.92	0.83	0.8	**0.79**	0.59863	0.447	0.51082	0.91	0.88	0.88	0.9	0.89	0.88	0.45	0.39	0.39	0.65755	0.47528	**0.54674**
Kerala Floods	0.87	0.83	0.84	0.89	0.9	0.88	0.69	0.69	**0.66**	0.77004	0.52207	0.61486	0.93	0.88	0.89	0.93	0.93	0.92	0.29	0.3	0.27	0.73071	0.52681	**0.6092**
Hurricane Florence	0.77	0.73	0.74	0.8	0.78	0.78	0.43	0.55	0.47	0.72376	0.45858	**0.55706**	0.77	0.75	0.75	0.81	0.8	0.79	0.13	0.14	0.13	0.71954	0.46799	**0.56453**
California Wildfires	0.91	0.89	0.89	0.92	0.93	0.92	0.72	0.77	**0.73**	0.70802	0.37375	0.48741	0.92	0.89	0.9	0.9	0.9	0.89	0.3	0.33	0.3	0.68827	0.35958	**0.46522**
Cyclone Idai	0.93	0.88	0.89	0.94	0.92	0.92	0.26	0.23	0.24	0.69456	0.47548	**0.56195**	0.91	0.87	0.88	0.91	0.9	0.9	0.17	0.17	0.17	0.72166	0.49704	**0.58403**
Midwestern U.S. Floods	0.96	0.91	0.92	0.94	0.95	0.94	0.66	0.76	**0.68**	0.7366	0.46284	0.56618	0.97	0.91	0.92	0.95	0.97	0.95	0.44	0.54	0.44	0.74625	0.40682	**0.52307**
Hurricane Dorian	0.86	0.85	0.85	0.87	0.89	0.87	0.58	0.62	**0.59**	0.8005	0.46873	0.58913	0.8	0.77	0.77	0.88	0.88	0.87	0.14	0.14	0.14	0.79192	0.43256	**0.55806**
Pakistan Earthquake	0.9	0.89	0.88	0.89	0.91	0.89	0.5	0.34	0.38	0.65954	0.5459	**0.59613**	0.87	0.87	0.85	0.86	0.9	0.87	0.11	0.08	0.09	0.66113	0.52942	**0.58738**



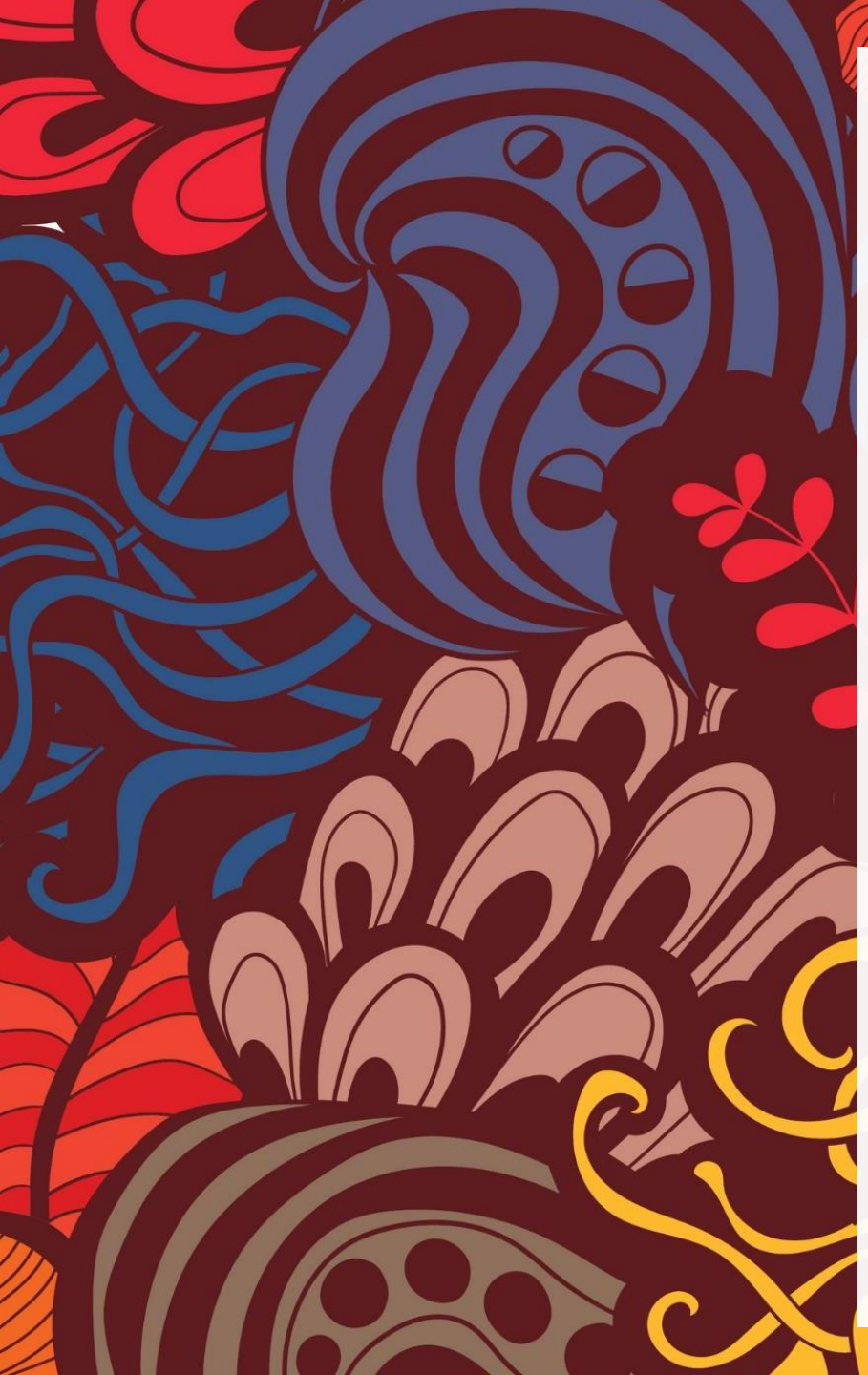
Analysis

- Low recall due to dataset haven't consider sub location but model predicts.
- Model consider special character as words and provide prediction over them.
- Model consider similar spelled words as location such as ‘us’ & ‘US’ are similar.

Learning & Future Directions

- **Learnings:**
  - ➢ Dataset exploration
  - ➢ POS handling to get the desired information from text
  - ➢ Pretrained Embeddings from different models & their behavior.
  - ➢ LSTM, RNN, BERT, Attention-model & their development & behavior towards sequential data.

- **Future Direction:**
  - ➢ Extracting some other information in similar fashion from various plateforms & provide real time alerts of them.
  - ➢ Adding Google's gdelt project for extracting real time information from current news.



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Thankyou.

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