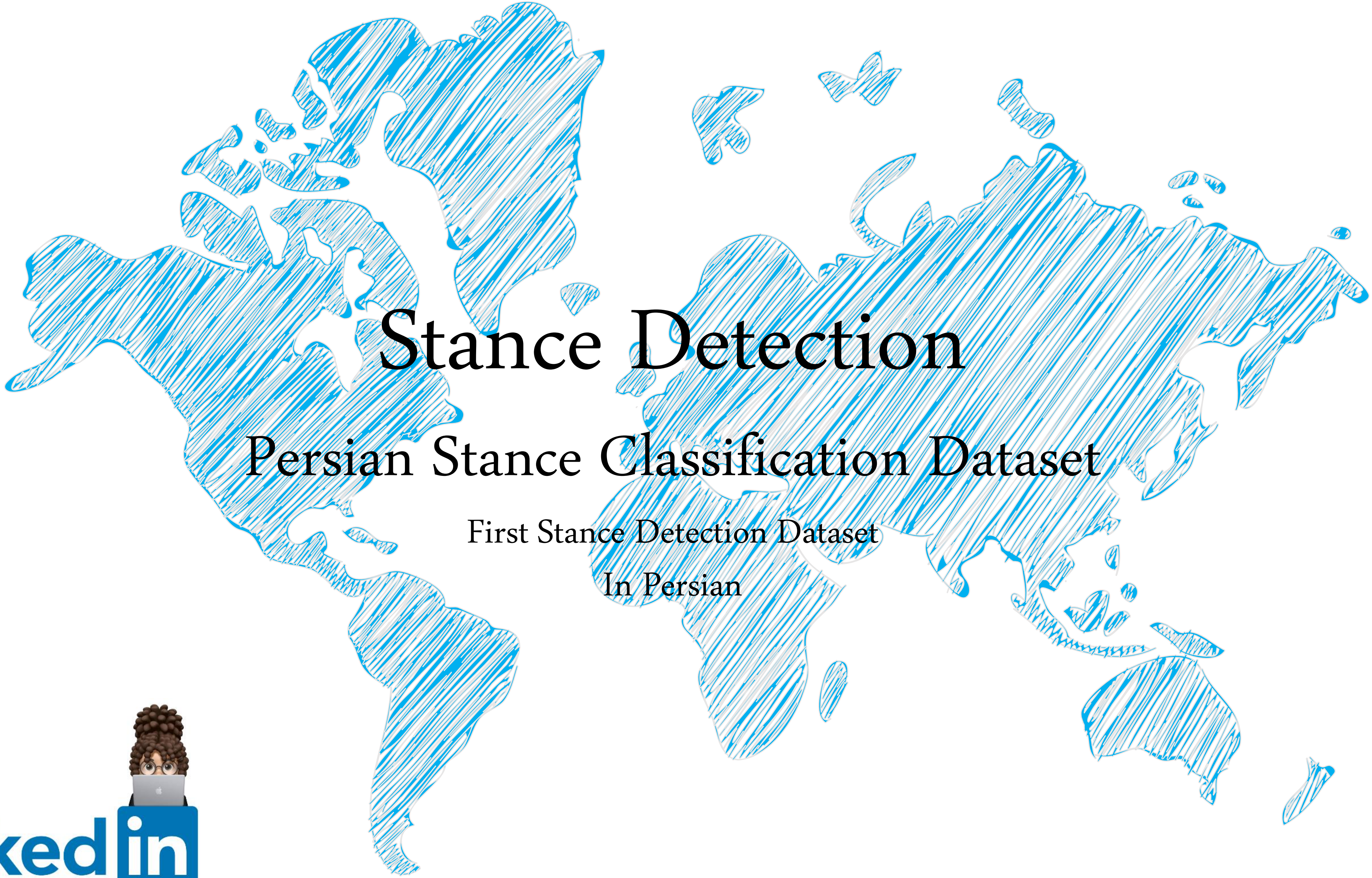


Stance Detection

Persian Stance Classification Dataset

First Stance Detection Dataset

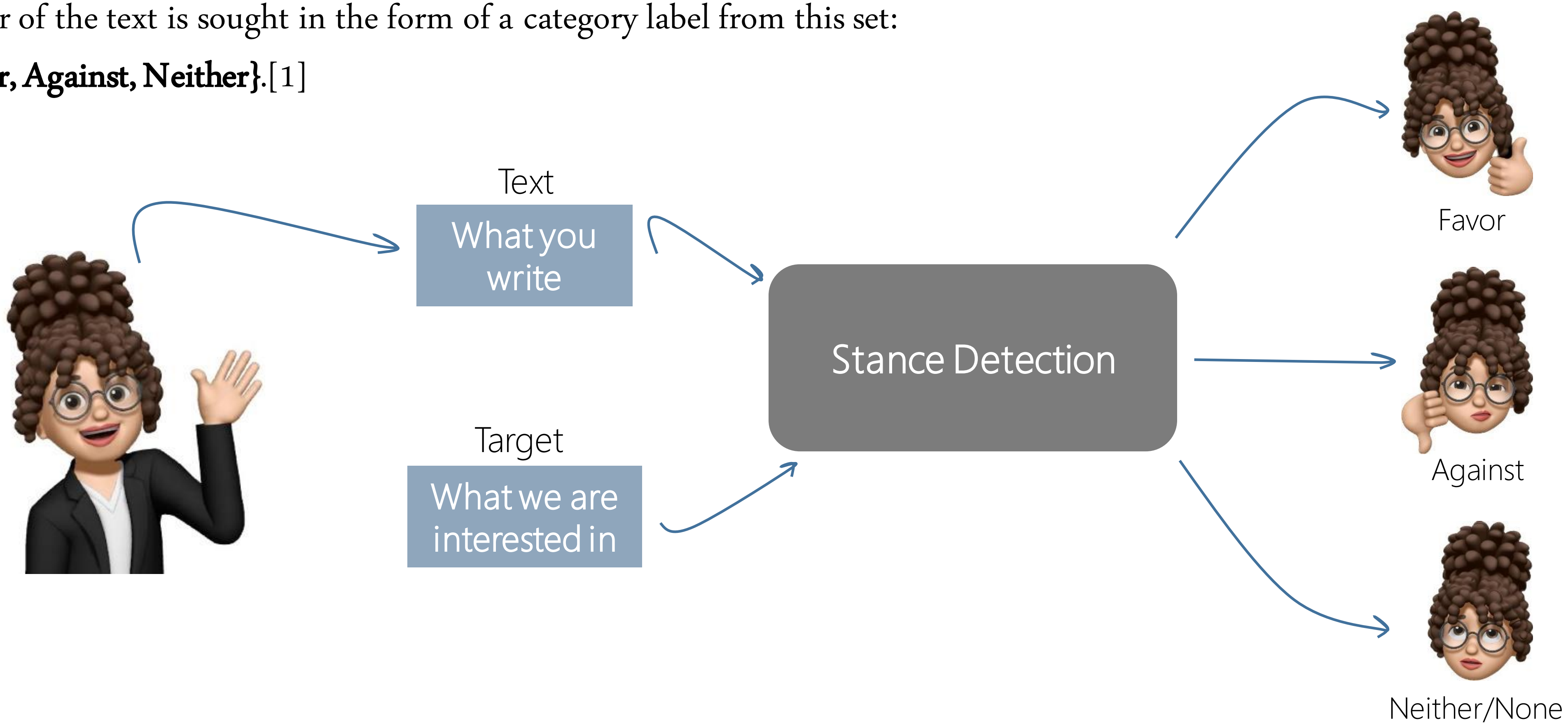
In Persian

LinkedIn

Stance Detection

For an input in the form of a piece of text and a target pair, stance detection is a classification problem where the stance of the author of the text is sought in the form of a category label from this set:

{Favor, Against, Neither}.[1]

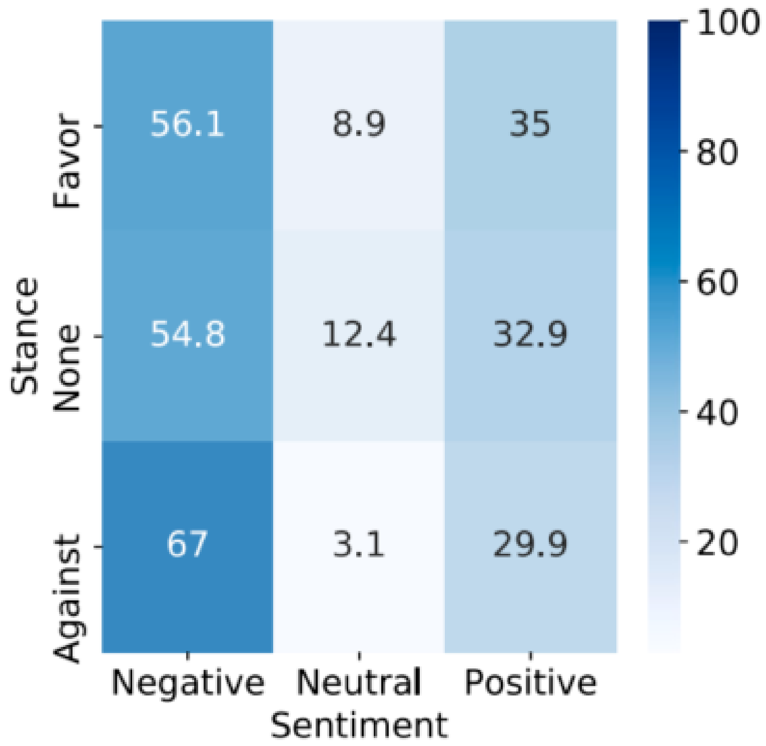


Stance Detection Vs Sentiment Analysis

#	Tweet	Target	Sentiment	Stance
1	It is so much fun having younger friends who are expecting babies. #beentheredonethat #chooselife .	Legalisation of Abortion	+	-
2	Life is sacred on all levels. Abortion does not compute with my philosophy. (Red on #OITNB)	Legalization of Abortion	0	-
3	The biggest terror threat in the World is climate change #drought #floods	Climate Change is the real concern	-	+
4	I am sad that Hillary lost this presidential race	Hillary Clinton	-	+

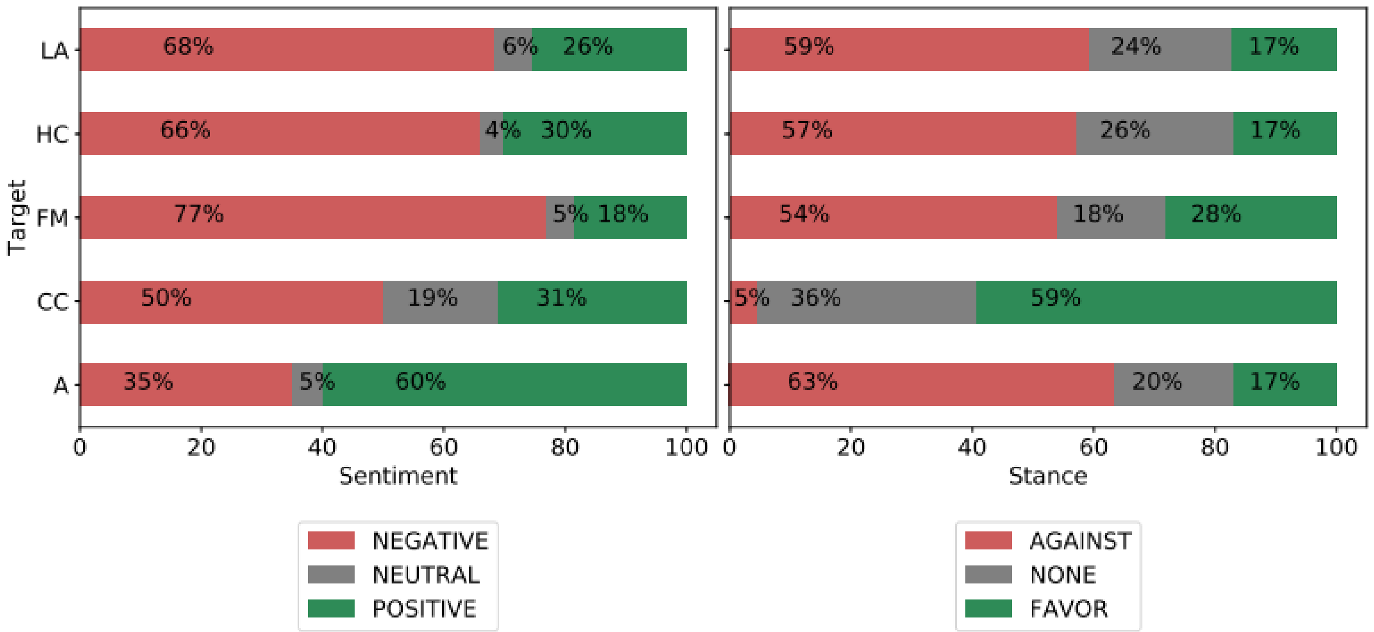
Table 1. sample of tweets illustrating the sentiment polarity of the expressed stance [3]

4	I am sad that Hillary lost this presidential race	Hillary Clinton	-	+



Sentiment distribution over stance [3]

Illustrates the sentiment distribution on stances for the whole collection (favor, against, and none) in dataset SEM-Eval2016.[3]



Sentiment and stance distribution [3]

'Atheism' (A),
'Climate change is a real concern' (CC)
'Feminist movement' (FM),
'Hillary Clinton' (HC),
and 'Legalization of abortion' (LA)

Aspect-Oriented (or Aspect-Based, or Aspect-Level) Sentiment Analysis

In this subproblem of sentiment analysis, the sentiment polarities towards a target entity and different aspects of this entity are considered in a given text input.

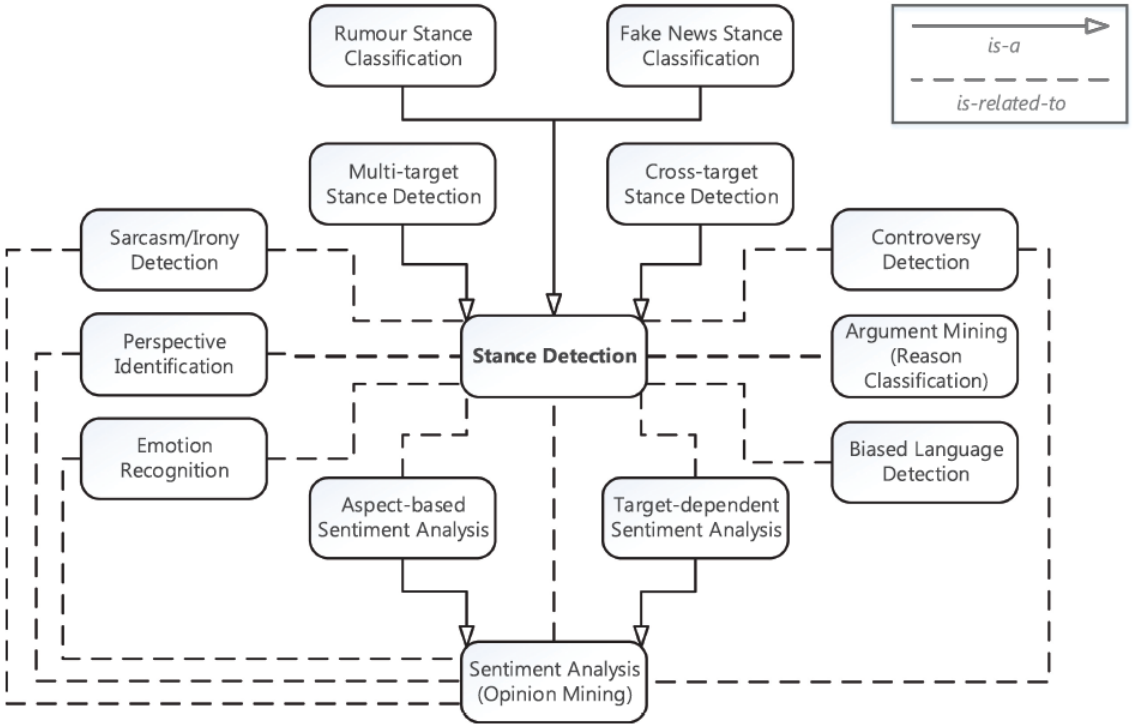
Target-Dependent (or Target-Based) Sentiment Analysis

In this subproblem of sentiment analysis, the sentiment polarity towards the target is explored within the text, given a text and target pair.

(1) The stance target may not be explicitly given in the input text,

(2) The stance target may not be the target of the sentiment in the text.

(3) The stance target may be an event while the target is usually an entity or an aspect in sentiment analysis.



Research problems related to stance detection and subproblems of stance detection.

Stance Detection According To Target

Target-specific Stance Detection

The basic form of stance detection on social media is the target-specific stance detection. Most of the previous studies focused on inferring the stance for a set of predefined targets. In this type of stance detection, the text (T) or the user (U) is the main input to predict the stance toward a specific predefined single target (G).

$$Stance(T \mid U, G) = \{Favor, Against, None\}$$

Multi-Related-Target Stance Detection

In multi-target stance detection, the goal is to jointly learn the social media users' orientation toward two or more targets for a single topic.
The main assumption behind this kind of stance detection is that when a person gives their stance for one target, it provides information on their stance toward other related targets.

$$Stance(T \mid U, G_n) = \{(Favour G_1, Against G_{n+1}), (Favourof G_{n+1}, Against G_1)\}$$

Claim-Based Stance Detection

In claim-based or open-domain stance detection, the target of the analysis is not an explicit entity, as is the case in the ones discussed earlier. This, however, is a claim in a piece of news. The first stage to detect a stance is to identify the main target claim from the sequence of conversation or given text. The main input to the claim-based stance detection model is the claim (C), which could be the rumor's post or based on an article headline.

Claim: Kamal Kharrazi meeting with John Kerry in Paris ملاقات کمال خرازی با جان کری در پاریس
Headline: Kamal Kharrazi encounters with John Kerry in Paris دیدار کمال خرازی و جان کری در پاریس **Stance**: Agree
Headline: The visit of Kamal Kharrazi to John Kerry was denied تکذیب خبر دیدار کمال خرازی با جان کری **Stance**: Discuss
Headline: The news of Kharrazi meeting with John Kerry is a big lie خبر دیدار خرازی با کری دروغ محض است **Stance:** Disagree
Headline: Kamal Kharrazi said that Iran seeks peace and stability in the region کمال خرازی عنوان کرد که ایران به دنبال صلح و آرامش در منطقه است **Stance**: Unrelated
Veracity: False

Example of stance detection in Persian Dataset [4]

1. Fake News Stance Detection

In the fake news task, the claim tends to be the article headline (H,C) and the text is the article body (T).

$$Stance(T \mid H,C) = \{Agree, Disagree, Discuss, Unrelated\}$$

2. Rumer Stance Detection

For the rumor's veracity task, the main input to be evaluated is the rumor's post, while the text is the replies to the rumors. The prediction label sets tend to take the form of supporting the claim or denying it.

$$Stance(T \mid C) = \{Supporting, Denying, Querying, Commenting\}$$

Stance Detection Applications

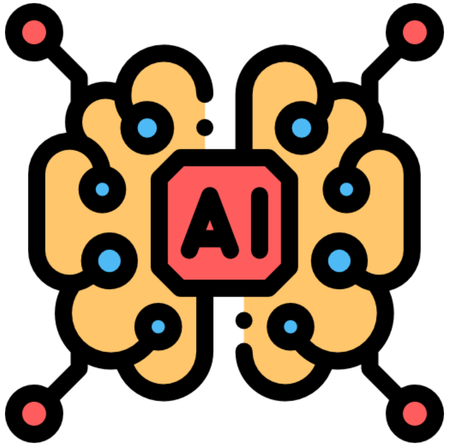
- Public opinion polls
- Recommender Systems
- Targeted Advertising
- Fake News Detection

Social Media

Social media is a collective term for websites and applications that focus on communication, community-based input, interaction, content-sharing and collaboration. People use social media to stay in touch and interact with friends, family and various communities.

Artificial Intelligence

Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems. Specific applications of AI include expert systems, natural language processing, speech recognition and machine vision.



Natural Language Processing (NLP)

Word Embedding

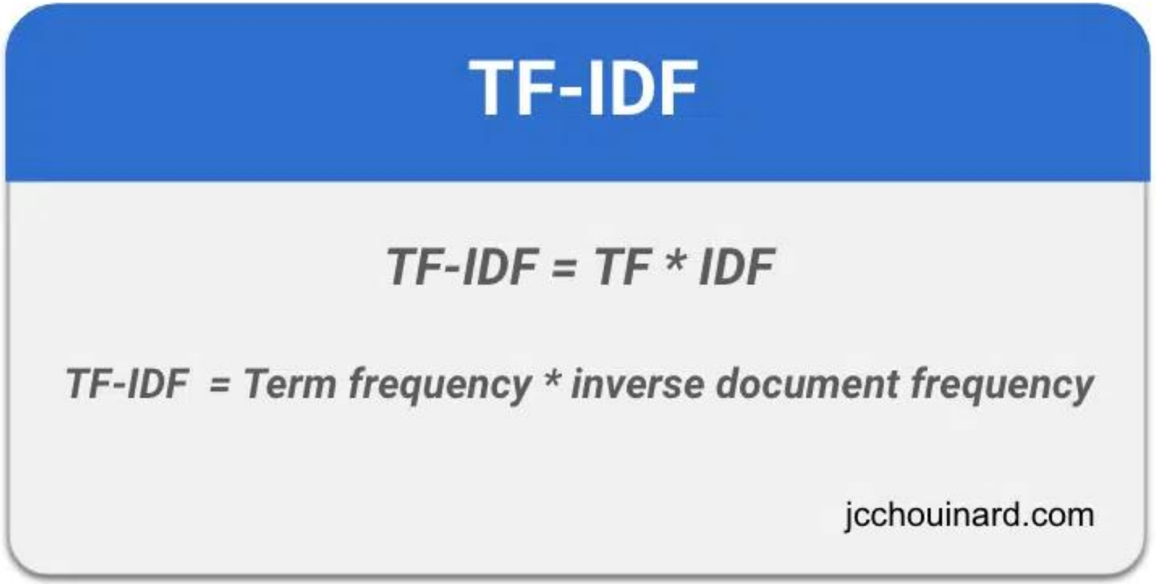
In natural language processing (NLP), a word embedding is a representation of a word. The embedding is used in text analysis.

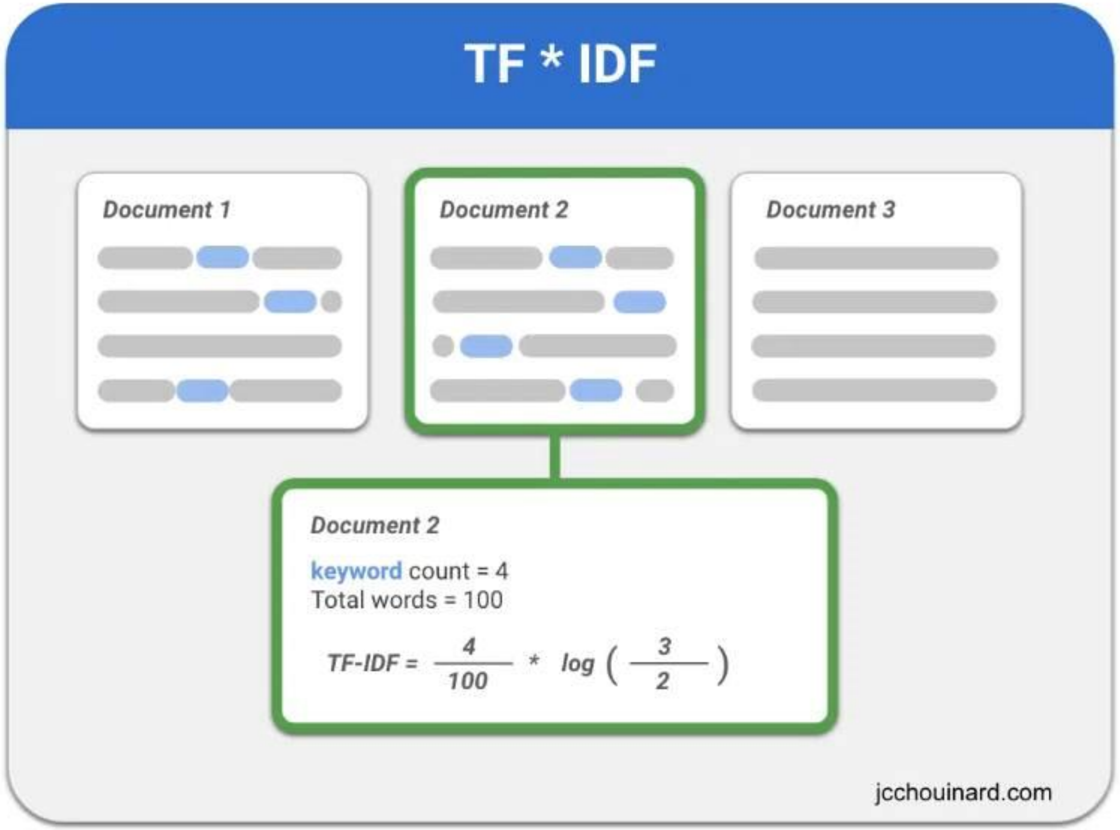
One-hot Encoding

One Hot Encoding

color	color_red	color_blue	color_green
red	1	0	0
green	0	0	1
blue	0	1	0
red	1	0	0

Term Frequent-Inverse Document Frequency (TF-IDF)

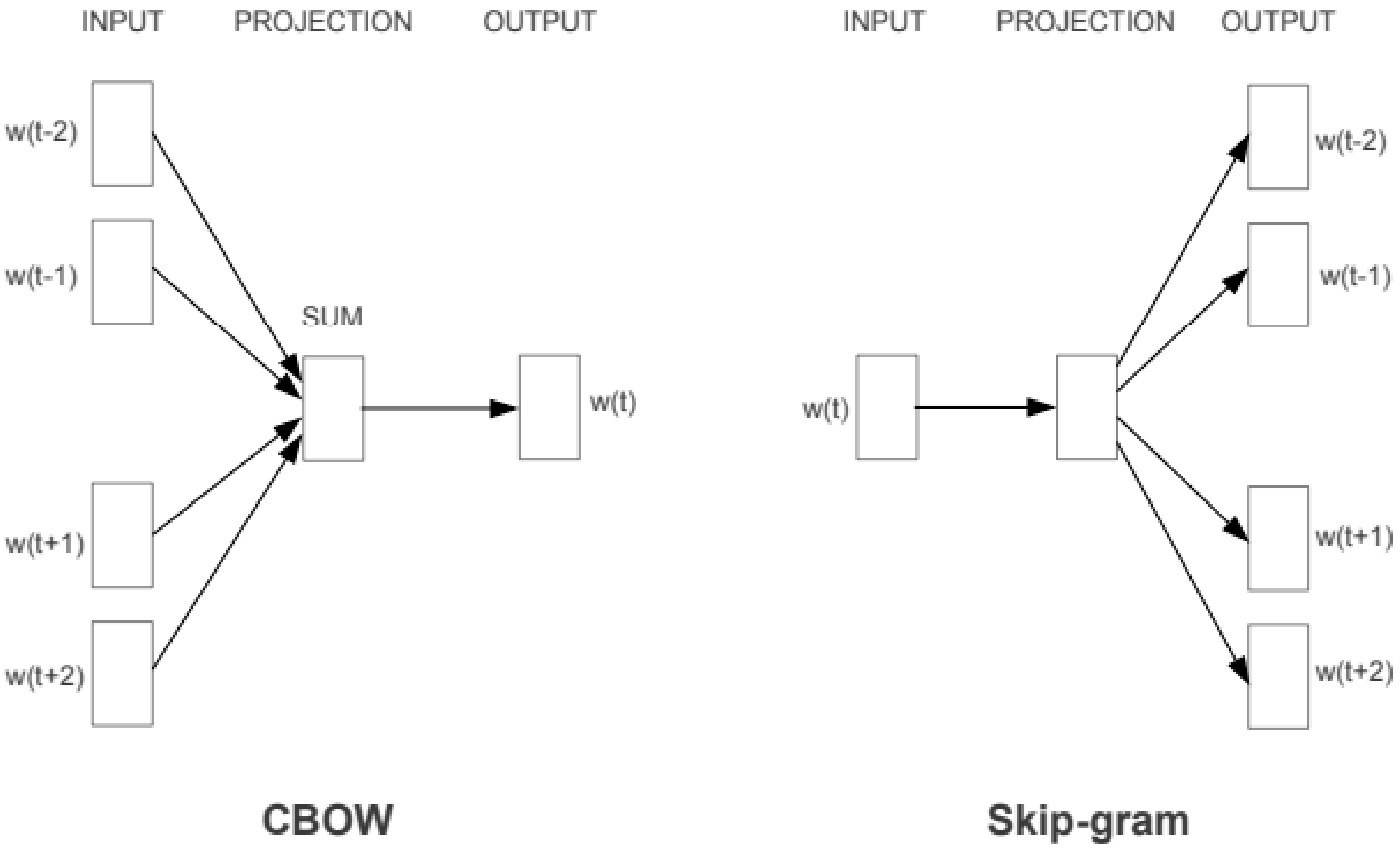




Word2Vec

1. CBOW

2. Skip Gram



Glove

A co-occurrence matrix tells us how often a particular pair of words occur together. Each value in a co-occurrence matrix is a count of a pair of words occurring together.

1. I play cricket.
2. I love cricket
3. I love football

Number of times word j appears in contxt of word i

X_{ij} Element .ex. $X_{13} = 2$

X

	Play	Love	Football	I	Cricket
Play	0.0	0.0	0.0	1.0	1.0
Love	0.0	0.0	1.0	2.0	1.0
Football	0.0	1.0	0.0	0.0	0.0
I	1.0	2.0	0.0	0.0	0.0
Cricket	1.0	1.0	0.0	0.0	0.0

$X = X^T$

Symmetric matrix

$X_i = \Sigma X_{ik}$

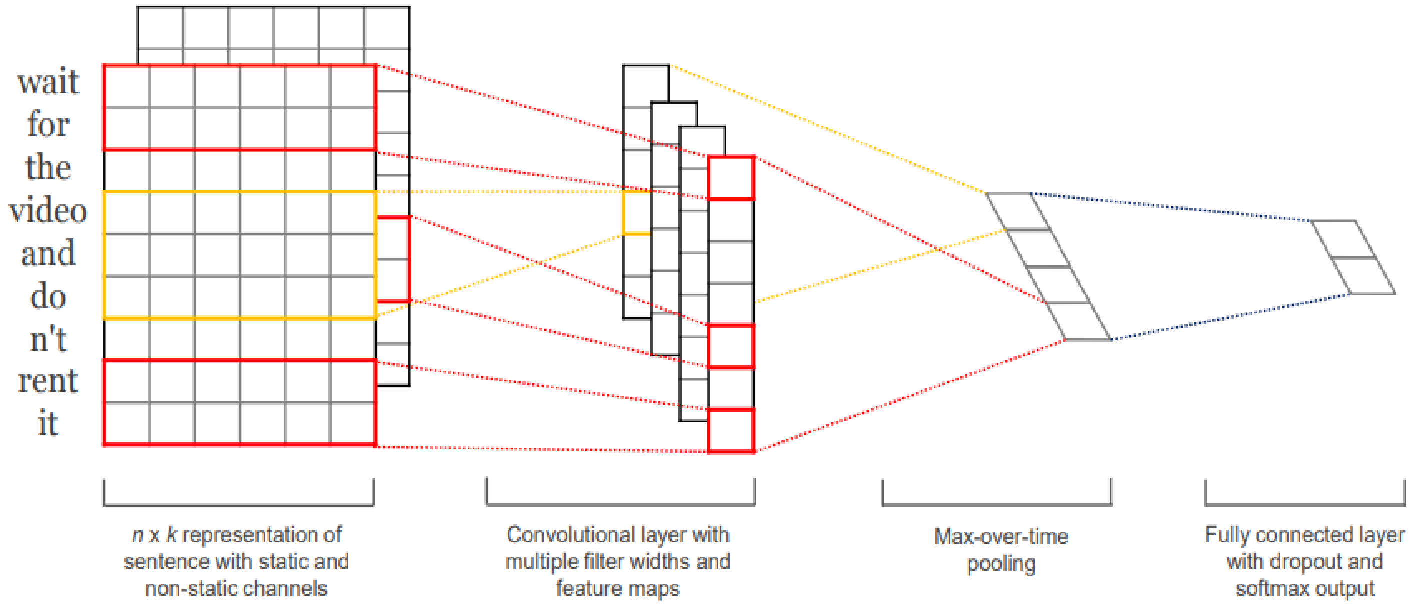
$P_{ij} = P(W_J \mid W_i) = \frac{X_{ij}}{X_i}$

$X_1 = 0 + 0 + 1 + 2 + 1 = 4$

$P_{13} = P(W_3 \mid W_1) = \frac{X_{13}}{X_1} = \frac{2}{4} = 0.5$

Generate text representation using CNN, GRU, LSTM

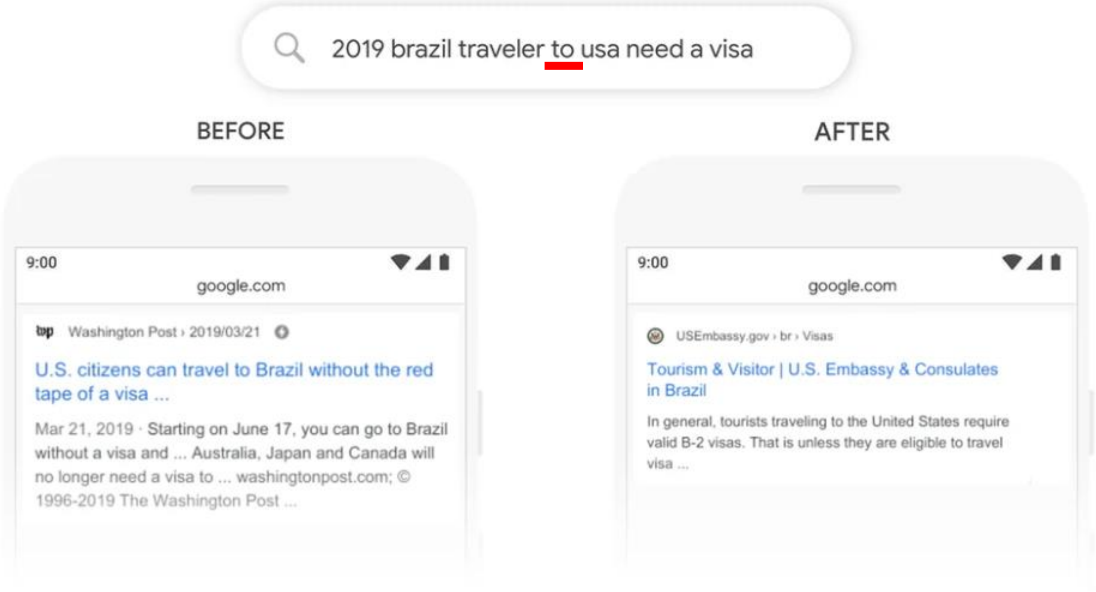
Convolutional Neural Network (CNN)

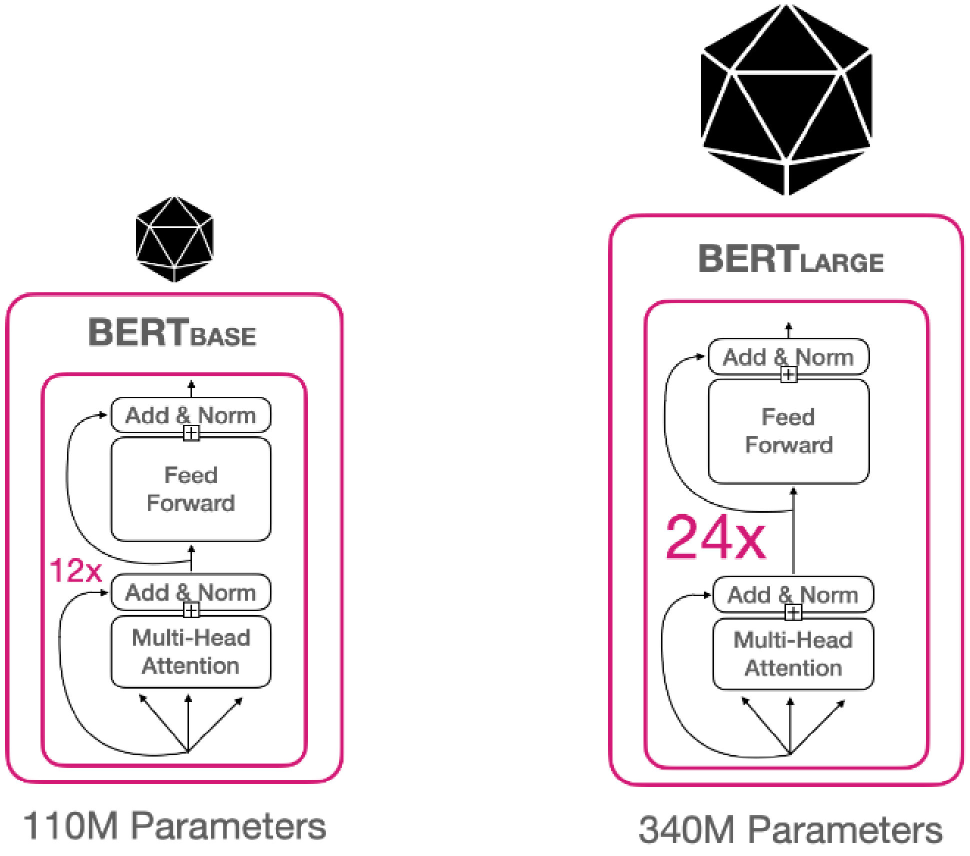


Generating text representation using the CNN Network [5]

BERT

BERT is an open source machine learning framework for NLP. BERT is designed to help computers understand the meaning of ambiguous language in text by using surrounding text to establish context.



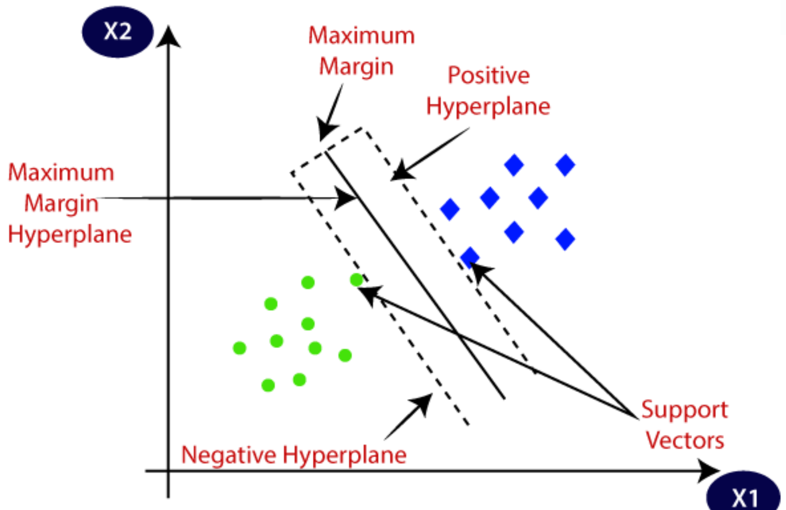


BERT Architecture

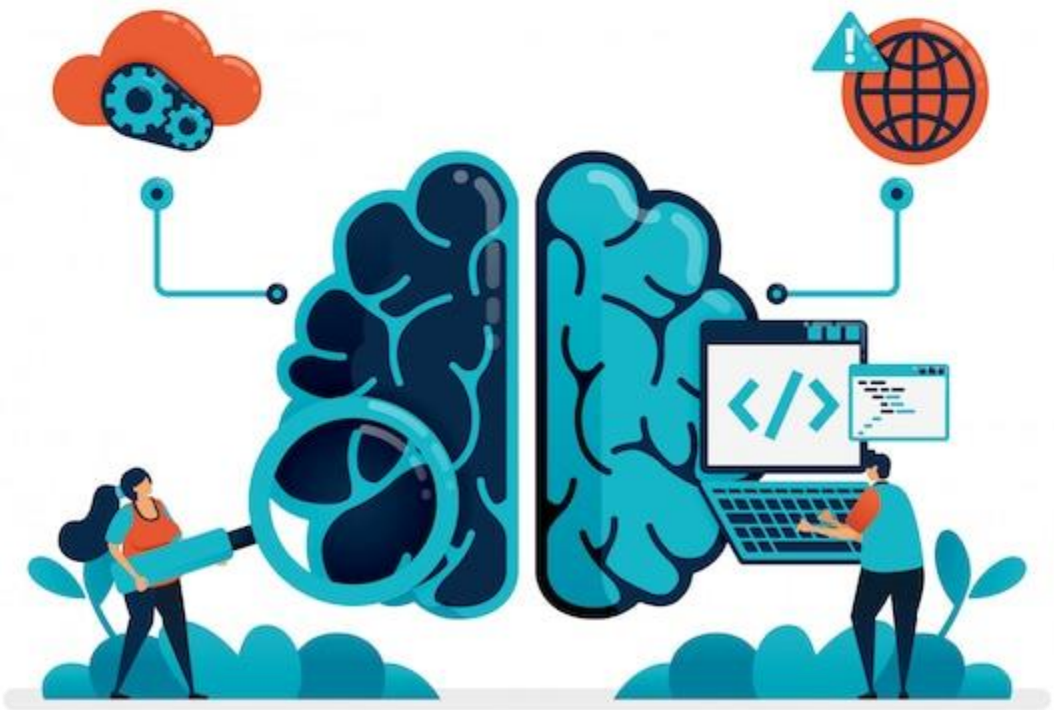
Machine learning

SVM

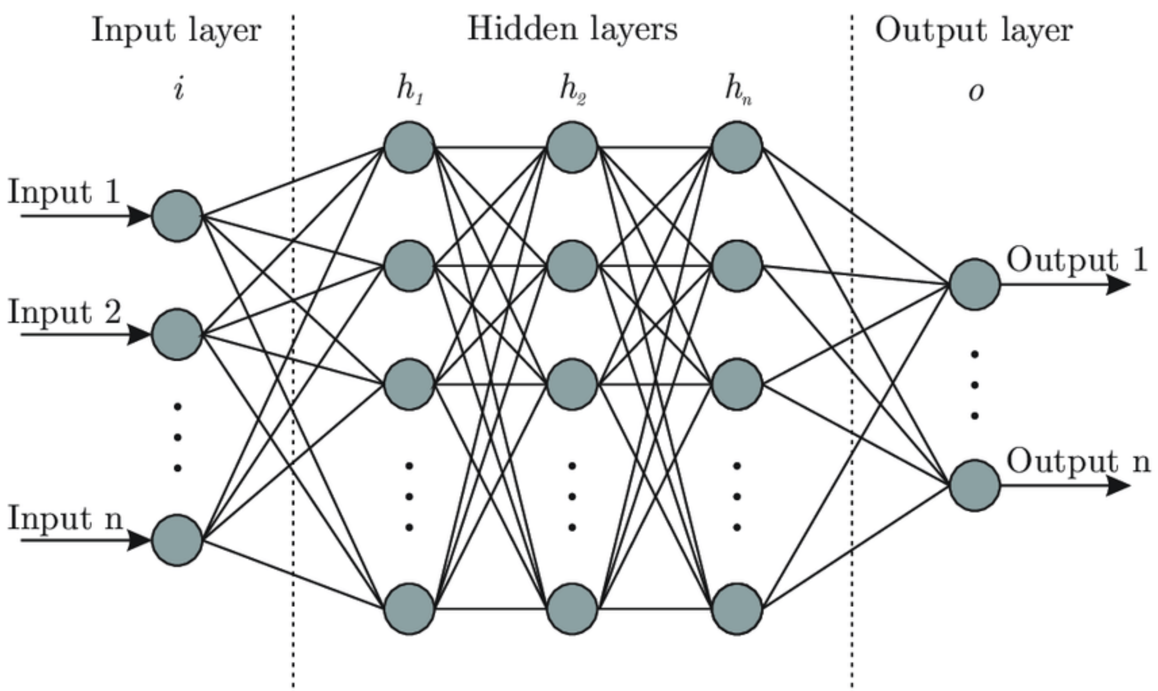
It is a supervised machine learning problem where we try to find a hyperplane that best separates the two classes.



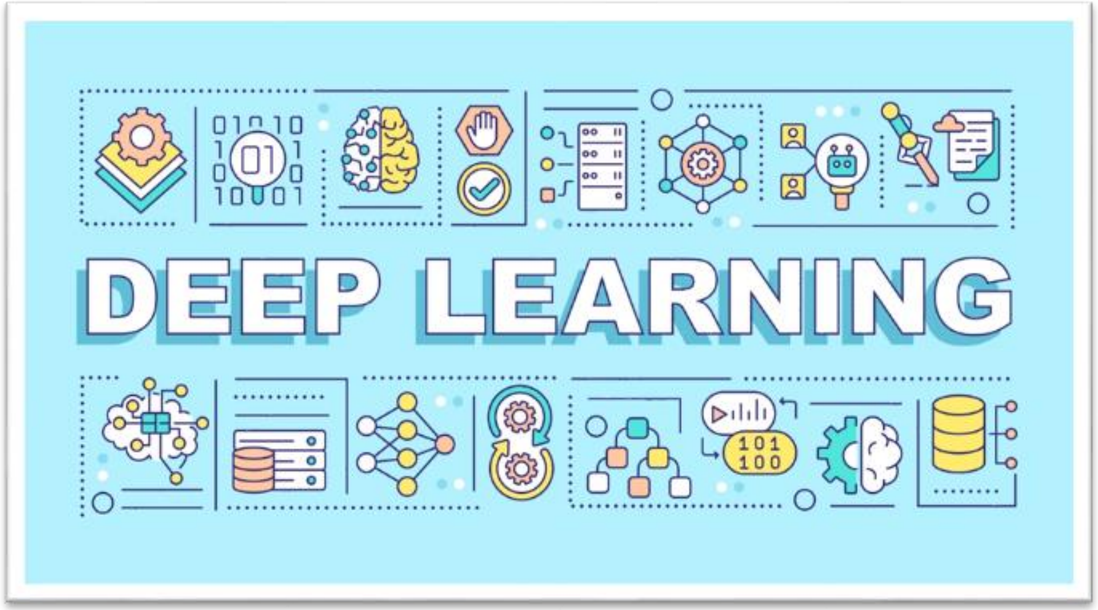
Example of Support Vector Machine



Deep Learning

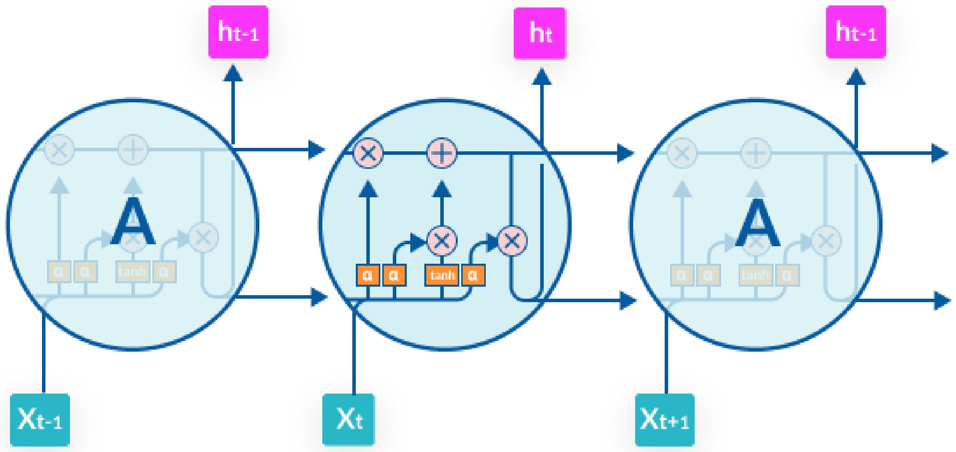


Example of Deep Neural Network



Recurrent Neural Network (RNN)

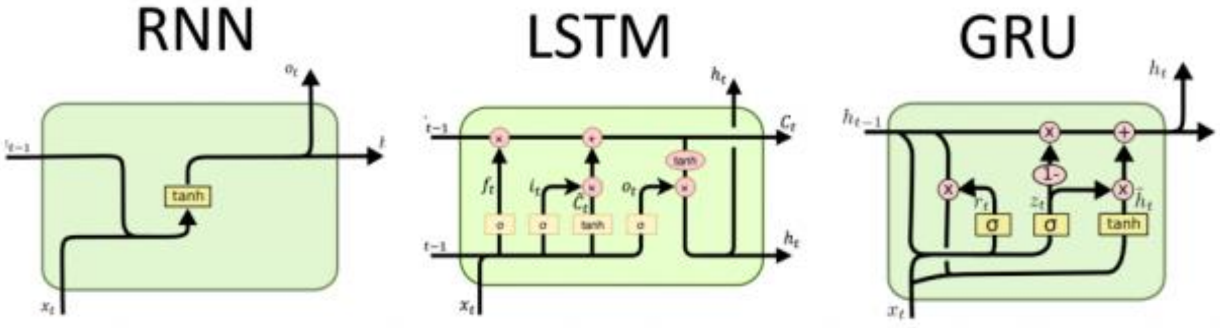
A recurrent neural network (RNN) is a type of artificial neural network which uses sequential data or time series data.



Recurrent Neural Networks: LSTM cells

LSTM Architecture

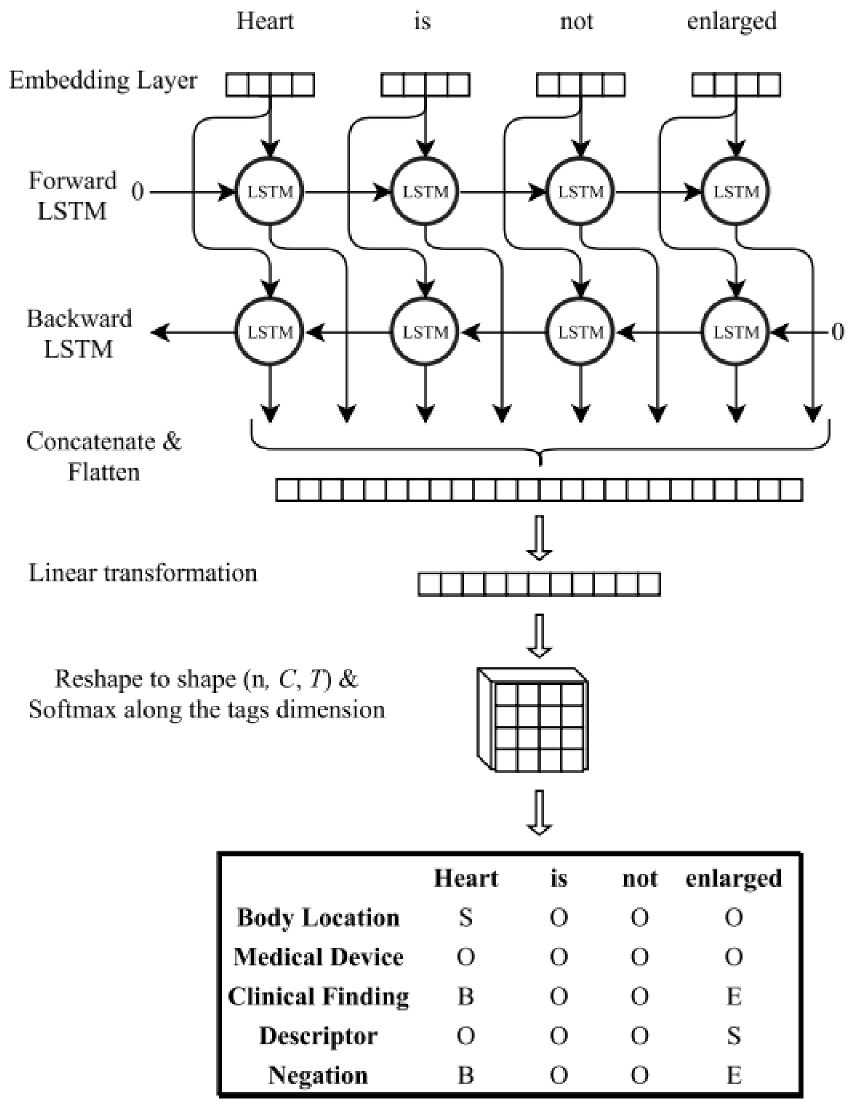
LSTM is a special type of recurrent neural network. Specifically, this architecture is introduced to solve the problem of vanishing and exploding gradients.



Comparison between RNN,LSTM,GRU [6]

BiLSTM Architecture

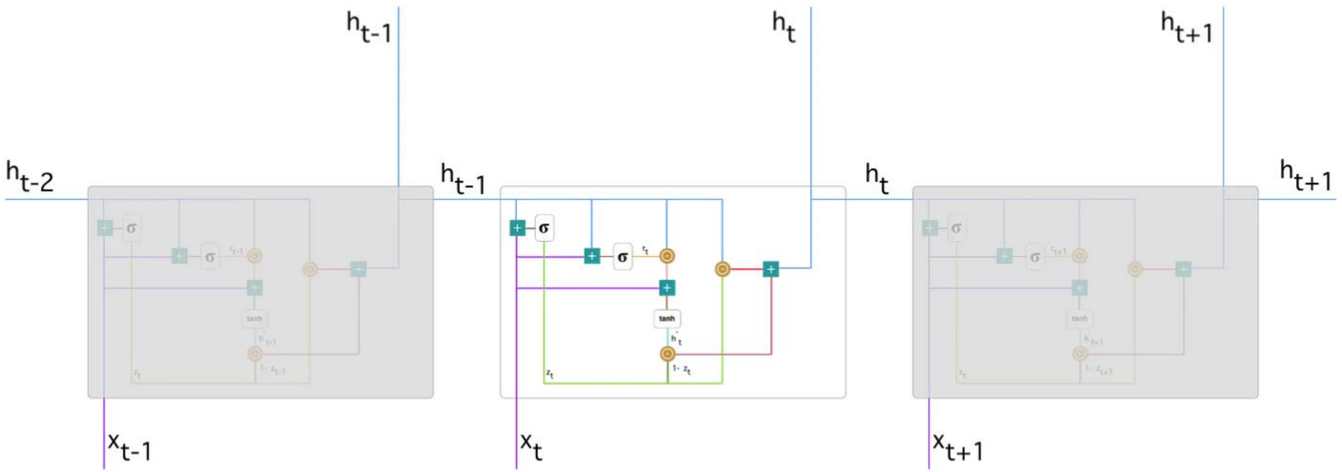
Bidirectional LSTM (BiLSTM) is a recurrent neural network used primarily on natural language processing. Unlike standard LSTM, the input flows in both directions, and it's capable of utilizing information from both sides.



BiLSTM Architecture[7]

Gated Recurrent Unit (GRU) Architecture

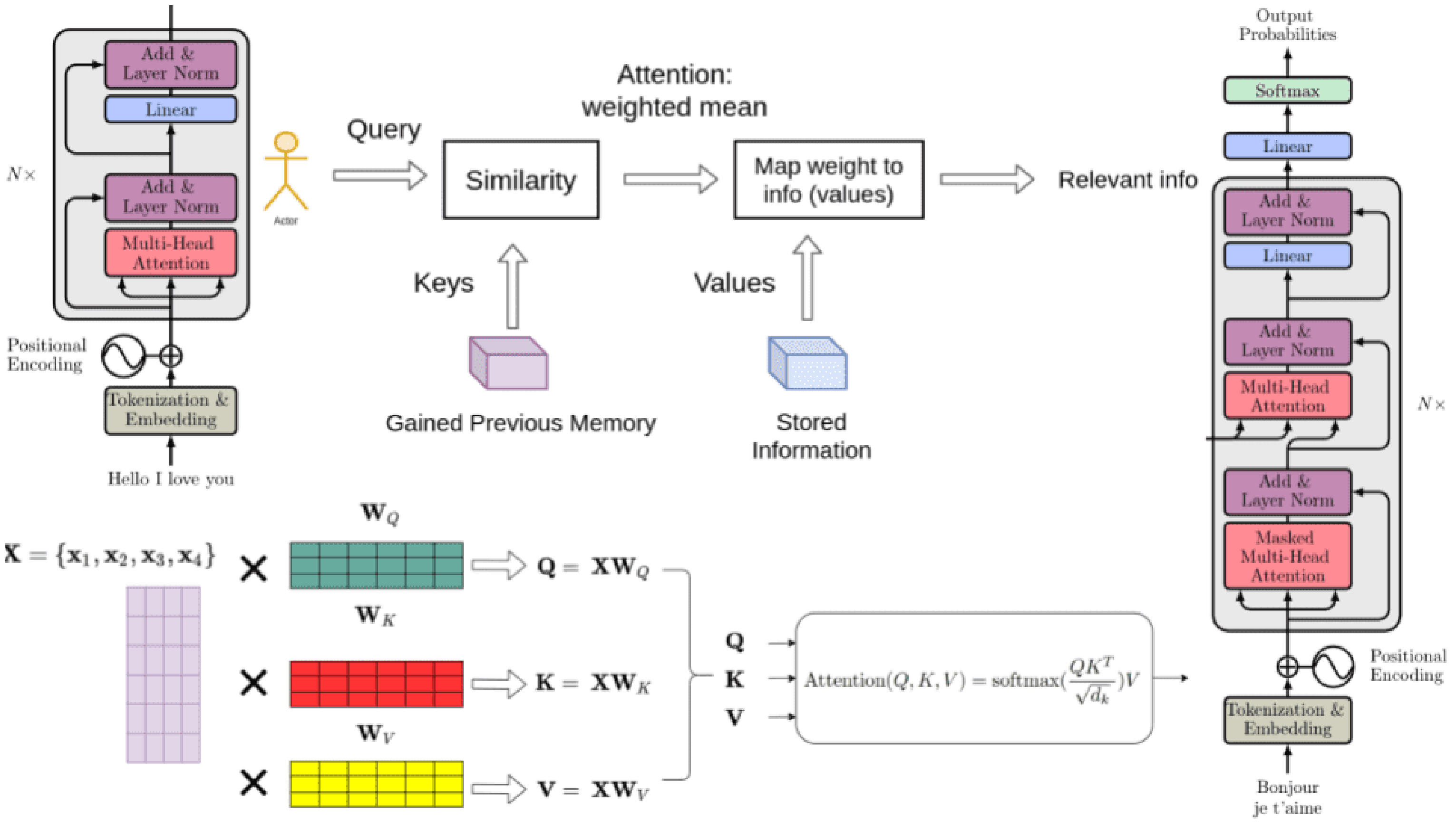
GRUs are very similar to LSTM. Just like LSTM, GRU uses gates to control the flow of information. Due to the simpler architecture, GRUs are faster to train.



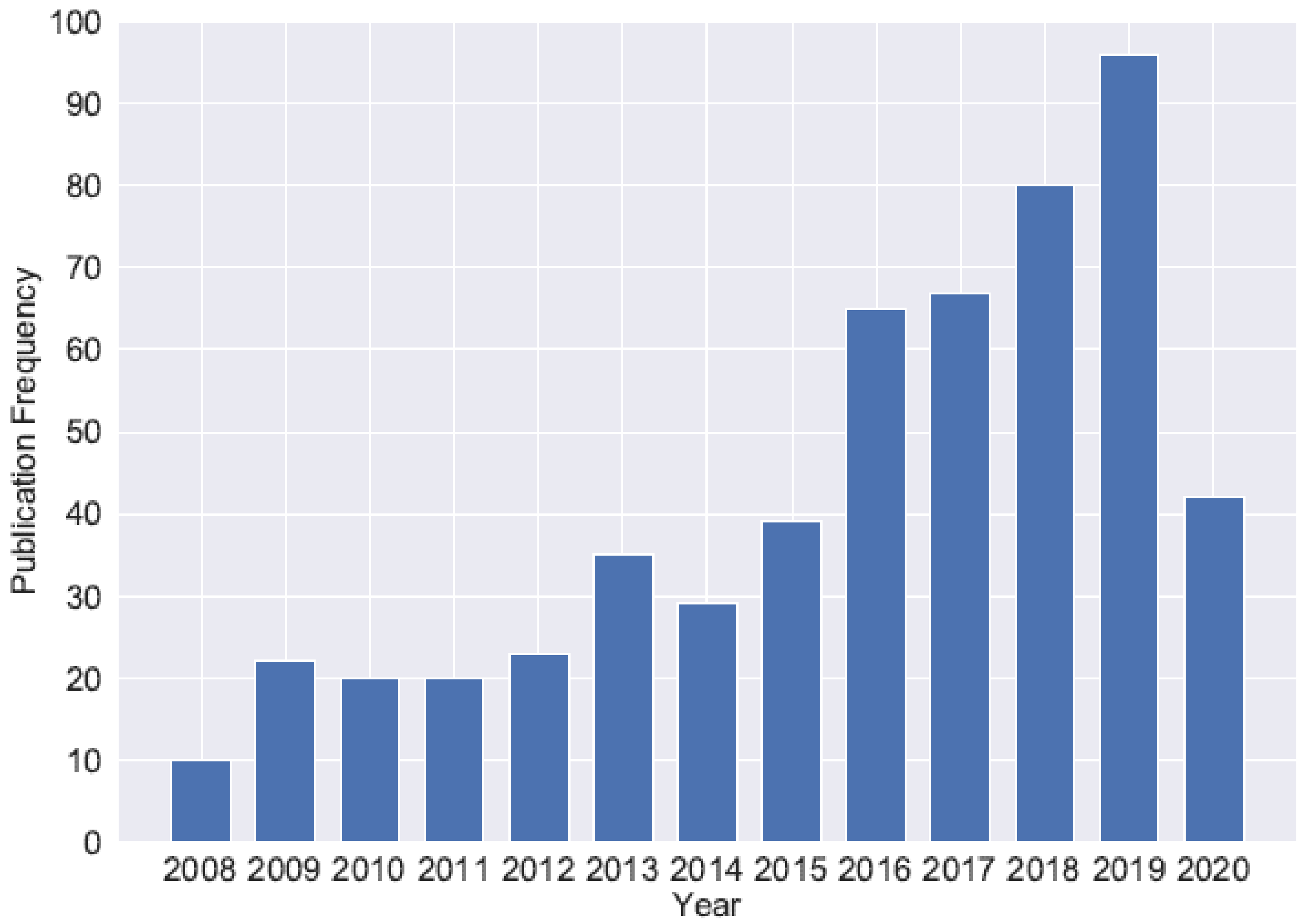
Recurrent neural network with Gated Recurrent Unit

Transformer

The Transformer in NLP is a **novel architecture** that aims to solve sequence-to-sequence tasks while handling long-range dependencies with ease. It relies entirely on self-attention to compute representations of its input and output WITHOUT using sequence-aligned RNNs or convolution.



Publications per year on stance detection as searched on Web of Science. The following keywords were used for search: “stance detection”, “stance prediction” and “stance classification”.[3]



Stance Detection Competitions

SemEval-2016 Task6 [8]

Detecting Stance in English Tweets.

Subtask A : Supervised Stance Detection

Number of Topics=5

Train Data=2814

Test Data=1249

Subtask B : Weakly Supervised Stance Detection

Train Data=78000 (without Lable)

Best Model : SVM

Best Model : RNN

Model : CNN

Team	Overall F_{favour}	Overall $F_{against}$	Overall F_{avg}	Atheism F_{avg}	Climate F_{avg}	Feminism F_{avg}	Hillary F_{avg}	Abortion F_{avg}
Baselines								
Majority class	52.01	**78.44**	65.22	42.11	42.12	39.10	36.83	40.30
SVM-unigrams	54.49	72.13	63.31	53.25	38.39	55.65	57.02	60.09
SVM-ngrams	**62.98**	74.98	**68.98**	**65.19**	42.35	**57.46**	**58.63**	**66.42**
SVM-ngrams-comb	54.11	70.01	62.06	53.27	**47.76**	52.82	56.50	63.71
Participating Teams								
MITRE	59.32	**76.33**	**67.82**	61.47	41.63	**62.09**	57.67	57.28
pkudblab	**61.98**	72.67	67.33	63.34	52.69	51.33	64.41	61.09
TakeLab	60.93	72.73	66.83	**67.25**	41.25	53.01	**67.12**	61.38
PKULCWM	56.96	74.55	65.76	56.39	40.39	51.32	62.26	61.56
ECNU	60.55	70.54	65.55	61.97	41.32	56.21	57.85	61.25
CU-GWU	54.99	72.21	63.60	55.68	39.41	53.88	51.19	59.38
IUCL-RF	52.61	74.59	63.60	57.93	39.06	51.06	49.84	57.61
DeepStance	58.44	68.65	63.54	52.90	40.40	52.34	55.35	**63.32**
UWB	57.41	69.42	63.42	57.88	46.90	51.82	59.82	61.98
IDI@NTNU	58.97	65.97	62.47	59.59	**54.86**	48.59	57.89	54.47
Tohoku	49.25	75.18	62.21	58.90	39.51	52.41	39.81	37.75
ltl.uni-due	48.71	74.75	61.73	52.47	35.50	55.12	44.23	57.25
LitisMind	50.67	72.20	61.44	52.36	39.15	57.16	42.08	45.88
JU_NLP	46.68	74.53	60.60	38.99	42.60	45.65	50.25	41.83
NEUSA	49.03	71.20	60.12	48.90	41.95	52.14	48.53	61.89
nldsucsc	50.90	67.81	59.36	57.19	42.10	48.97	57.27	61.66
WFU/TNT	47.55	70.89	59.22	46.16	42.07	47.91	45.88	45.34
INESC-ID	50.58	64.57	57.58	52.67	44.92	49.00	50.64	49.93
Thomson Reuters	30.16	62.23	46.19	44.79	35.86	39.37	34.98	38.89

Results for Task A

Best Model : CNN

Team	F_{favor}	$F_{against}$	F_{avg}
Baselines			
Majority class	0.00	59.44	29.72
SVM-ngrams-comb	18.42	38.45	28.43
Participating Teams			
pkudblab	**57.39**	55.17	**56.28**
LitisMind	30.04	**59.28**	44.66
INF-UFRGS	32.56	52.09	42.32
UWB	34.26	49.78	42.02
ECNU	17.96	50.20	34.08
USFD	10.93	54.46	32.70
Thomson Reuters	14.39	50.39	32.39
ltl.uni-due	46.56	05.71	26.14
NEUSA	16.59	34.87	25.73

Results for Task B

Tweet	Stance Target	Stance	Sentiment
RT @TheCLF: Thanks to everyone in Maine who contacted their legislators in support of #energyefficiency funding! #MEpoli #SemST	Climate Change is a Real Concern	Favor	Positive
We live in a sad world when wanting equality makes you a troll... #SemST	Feminist Movement	Favor	Negative
I don't believe in the hereafter. I believe in the here and now. #SemST	Atheism	Favor	Neither
@violencehurts @WomenCanSee The unborn also have rights #defendthe8th #SemST	Legalization of Abortion	Against	Positive
I'm conservative but I must admit I'd rather see @SenSanders as president than Mrs. Clinton. #stillvotingGOP #politics #SemST	Hillary Clinton	Against	Negative
I have my work and my faith... If that's boring to some people, I can't tell you how much I don't care. ~Madonna Ciccone #SemST	Atheism	Against	Neither
@BadgerGeno @kreichert27 @jackbahlman Too busy protesting :) #LoveForAll #BackdoorBadgers #SemST	Hillary Clinton	Neither	Positive
@ShowTruth You're truly unwelcome here. Please leave. #ygk #SemST	Legalization of Abortion	Neither	Negative
@Maisie_Williams everyone feels that way at times. Not just women #SemST	Atheism	Neither	Neither

Sample Tweets from SemEval 2016 Stance Dataset [1]

			% of instances in Train				% of instances in Test		
Target	**# total**	**# train**	favor	against	neither	**# test**	favor	against	neither
Data for Task A									
Atheism	733	513	17.9	59.3	22.8	220	14.5	72.7	12.7
Climate Change is Concern	564	395	53.7	3.8	42.5	169	72.8	6.5	20.7
Feminist Movement	949	664	31.6	49.4	19.0	285	20.4	64.2	15.4
Hillary Clinton	984	689	17.1	57.0	25.8	295	15.3	58.3	26.4
Legalization of Abortion	933	653	18.5	54.4	27.1	280	16.4	67.5	16.1
All	4163	2914	25.8	47.9	26.3	1249	24.3	57.3	18.4
Data for Task B									
Donald Trump	707	0	-	-	-	707	20.93	42.29	36.78

Distribution of instances in the Stance Train and Test sets for Task A and Task B. [8]

Shared Task of Stance Detection in Chinese Microblogs at **NLPCC-ICCPOL-2016** [9]

Subtask A : Supervised Stance Detection

Number of Topics=5

Subtask B : UnSupervised Stance Detection

Number of Topics=2

Data=2400

Models : SVM , Random Forest

Target	#Total	#Train	% of stances in Train			#Test	% of stances in Test		
			Favor	Against	None		Favor	Against	None
iPhone SE	800	600	40.8	34.8	24.3	200	37.5	52.0	10.5
Ban of fireworks	800	600	41.7	41.7	16.7	200	44.0	43.0	9.0
Russian anti-terrorist	800	600	41.7	41.7	16.7	200	47.0	43.0	10.0
Two-child Policy	800	600	43.3	33.3	23.3	200	49.5	47.5	3.0
Ban of Tricycles	800	600	26.7	50.0	23.3	200	31.5	55.0	13.5
Total	4000	3000	38.8	40.3	20.8	1000	41.9	48.1	10.0

Statistics of NLPCC stance detection dataset

Team ID	OVERALL			Target-1	Target-2	Target-3	Target-4	Target-5
	F_{FAVOR}	$F_{AGAINST}$	F_{AVG}	F_{AVG}	F_{AVG}	F_{AVG}	F_{AVG}	F_{AVG}
RUC_MMC	0.6969	0.7243	0.7106	0.7730	0.5780	0.5814	0.8036	0.7652
TopTeam	0.6601	0.7186	0.6894	0.7449	0.5764	0.5232	0.7661	0.7949
SDS	0.6758	0.6965	0.6861	0.7784	0.5852	0.5332	0.7948	0.6883
CBrain	0.6618	0.7094	0.6856	0.7604	0.5528	0.4787	0.8135	0.7855
nlp_polyu	0.6476	0.6870	0.6673	0.7354	0.5312	0.5584	0.7708	0.7090
Scau_SDCM*	0.6304	0.7027	0.6666	0.7033	0.5493	0.5780	0.7639	0.7138
NEUDM	0.6268	0.6858	0.6563	0.7173	0.5485	0.5240	0.7497	0.7052
Printf	0.6183	0.6702	0.6443	0.7048	0.5769	0.5547	0.7150	0.6417
CQUT_AC996	0.5897	0.6557	0.6227	0.7015	0.4646	0.5280	0.7661	0.5879
March*	0.5858	0.6244	0.6051	0.6950	0.5466	0.4906	0.6442	0.6169
BIT_NLP_FC*	0.5573	0.5833	0.5703	0.7444	0.3460	0.3769	0.5888	0.4195
HLJUNLP	0.4584	0.6729	0.5656	0.5281	0.4494	0.5126	0.7553	0.4355
CIST-BUPT	0.4660	0.6136	0.5398	0.4754	0.4579	0.5003	0.6867	0.5048
Lib1010	0.4636	0.4944	0.4790	0.4551	0.4420	0.4934	0.4946	0.5045
USCGreenTree*	0.3609	0.5904	0.4756	0.4799	0.4052	0.4586	0.5288	0.3871
SCHOOL	0.3329	0.4662	0.3995	0.3422	0.4222	0.3903	0.4613	0.3676

Evaluation results for Task A

Team ID	OVERALL			Target-6	Target-7
	F_{FAVOR}	$F_{AGAINST}$	F_{AVG}	F_{AVG}	F_{AVG}
March*	0.3707	0.5667	0.4687	0.5173	0.4165
BIT_NLP_FC*	0.2706	0.6137	0.4421	0.4485	0.4289
CQUT_AC996	0.2985	0.5455	0.4220	0.4562	0.3815
TopTeam	0.0000	0.6555	0.3277	0.3266	0.3289
NEUDM	0.2478	0.3987	0.3232	0.1730	0.3628

The team ID with * means late submission.

Evaluation results for Task B

Shared Task of Stance Detection in Spanish and Catalan Tweets at **IberEval-2017[10]**

A subsequent competition similar to SemEval-2016 and NLPCC-ICCPOL-2016 shared tasks on stance detection is conducted within the course of the IberEval-2017 conference which is a shared task on stance and gender detection from tweets in Spanish and Catalan.

Best Model : Logistic regression

Best Model : SVM

Catalan		
Position	Team.Run	F
1	iTACOS.2	0.4901
2	iTACOS.1	0.4885
3	*majority class.baseline*	*0.4882*
4	iTACOS.3	0.4685
5	LTRC_IIITH.system1	0.4675
6	ARA1337.s1	0.4659
7	ARA1337.s2	0.4511
8	iTACOS.4	0.4490
9	iTACOS.5	0.4484
10	ATeam.systemid	0.4439
11	LTRC_IIITH.system3	0.4393
12	LTRC_IIITH.system4	0.4388
13	*LDR.baseline*	*0.4375*
14	LTL_UNI_DUE.hybrid	0.4246
15	LTL_UNI_DUE.svm	0.4233
16	LTRC_IIITH.system2	0.4233
17	LTRC_IIITH.system5	0.4165
18	UPF-LaSTUS.2	0.3955
19	UPF-LaSTUS.1	0.3949
20	UPF-LaSTUS.3	0.3938
21	LuSer.1	0.3909
22	UPF-LaSTUS.4	0.3854
23	deepCybErNet.2	0.3790
24	LTL_UNI_DUE.lstm	0.3726
25	deepCybErNet.1	0.3603
26	attope.2	0.3310
27	deepCybErNet.3	0.3257
28	attope.5	0.3120
29	attope.3	0.2970
30	attope.4	0.2910
31	attope.1	0.2710
32	ELIRF-UPV.1	-
33	ELIRF-UPV.2	-

Spanish		
Position	Team.Run	F
1	iTACOS.1	0.4888
2	LTRC_IIITH.system1	0.4679
3	LTRC_IIITH.system4	0.4640
4	ELIRF-UPV.1	0.4637
5	ELIRF-UPV.2	0.4637
6	UPF-LaSTUS.1	0.4600
7	iTACOS.2	0.4593
8	LTRC_IIITH.system2	0.4566
9	LTRC_IIITH.system3	0.4552
10	LTRC_IIITH.system5	0.4544
11	ARA1337.s1	0.4530
12	iTACOS.3	0.4528
13	*majority class.baseline*	*0.4479*
14	iTACOS.4	0.4427
15	LTL_UNI_DUE.hybrid	0.4347
16	LTL_UNI_DUE.svm	0.4314
17	ARA1337.s2	0.4313
18	iTACOS.5	0.4293
19	*LDR.baseline*	*0.4135*
20	LuSer.1	0.4060
21	ATeam.systemid	0.3914
22	UPF-LaSTUS.4	0.3812
23	UPF-LaSTUS.2	0.3795
24	deepCybErNet.3	0.3066
25	deepCybErNet.2	0.3042
26	deepCybErNet.1	0.2849
27	LTL_UNI_DUE.lstm	0.2759
28	UPF-LaSTUS.3	0.2505
29	attope.5	0.2466
30	attope.4	0.2438
31	attope.3	0.2426
32	attope.2	0.2074
33	attope.1	0.1906

Evaluation results for Stance in Catalan and Spanish (F-score)

SardiStance@EVALITA- 2020[11]

First Stance Detection Dataset In Italian Language.

Number of Tweets=3242

- Task A : Textual Stance Detection
- Task B : Contextual Stance Detection

	nodes	edges
friend	669,817	3,076,281
retweet	110,315	575,460
quote	2,903	7,899
reply	14,268	29,939

Networks metrics

team name	run	F1-score			
		AVG	AGAINST	FAVOUR	NONE
IXA	3	**.7445**	**.8562**	**.6329**	.4214
TextWiller	1	.7309	.8505	.6114	.2963
DeepReading	1	.7230	.8368	.6093	.3364
DeepReading	2	.7222	.8300	.6143	**.4251**
TextWiller	2	.7147	.8298	.5995	.3680
QMUL-SDS	1	.7088	.8267	.5908	.1811
UNED	2	.6888	.8175	.5600	.2455
QMUL-SDS	2	.6765	.8134	.5396	.1553
SSNCSE-NLP	2	.6582	.7915	.5249	.3691
SSNCSE-NLP	1	.6556	.7914	.5198	.3880
baseline		*.6284*	*.7672*	*.4895*	*.3009*
GhostWriter	1	.6257	.7502	.5012	.3810
GhostWriter	2	.6004	.7224	.4784	.3778
UNED	1	.5313	.7399	.3226	.2000

Results Task B

Best Model : BERT

team name	run	F1-score			
		AVG	AGAINST	FAVOUR	NONE
UNITOR	1	**.6853**	.7866	**.5840**	.3910
UNITOR	1	**.6801**	.7881	**.5721**	.3979
UNITOR	2	.6793	**.7939**	.5647	.3672
DeepReading	1	.6621	.7580	.5663	**.4213**
UNITOR	2	.6606	.7689	.5522	.3702
IXA	1	.6473	.7616	.5330	.3888
GhostWriter	1	.6257	.7502	.5012	.3810
IXA	2	.6171	.7543	.4800	.3675
SSNCSE-NLP	2	.6067	.7723	.4412	.2113
DeepReading	2	.6004	.6966	.5042	.3916
GhostWriter	2	.6004	.7224	.4784	.3778
UninaStudents	1	.5886	.7850	.3922	.2326
baseline		*.5784*	*.7158*	*.4409*	*.2764*
TextWiller	1	.5773	.7755	.3791	.1849
SSNCSE-NLP	1	.5749	.7307	.4192	.3388
QMUL-SDS	1	.5595	.7091	.4099	.2313
QMUL-SDS	2	.5329	.6478	.4181	.3049
MeSoVe	1	.4989	.7336	.2642	.3118
TextWiller	2	.4715	.6713	.2718	.2884
SSN_NLP	1	.4707	.5763	.3651	.3364
SSN_NLP	2	.4473	.6545	.2402	.1913
Venses	1	.3882	.5325	.2438	.2022
Venses	2	.3637	.4564	.2710	.2387

Results Task A

VaxxStance@IberLEF - 2021 [12]

- Close Track
  - Textual
  - Contextual
- Open Track
- Zero-shot Track

F_{avg}	زبان	زیر مسئله	نام تیم
80.92	اسپانیایی	Close Track (Textual)	WordUp
76.53	اسپانیایی	Close Track (Textual)	BASELINE
74.10	اسپانیایی	Close Track (Textual)	MultiAztertest
67.38	اسپانیایی	Close Track (Textual)	SQYQP
57.34	باسکی	Close Track (Textual)	WordUp
54.41	باسکی	Close Track (Textual)	BASELINE
50.24	باسکی	Close Track (Textual)	MultiAztertest
42.56	باسکی	Close Track (Textual)	SQYQP
89.13	اسپانیایی	Close Track (Contextual)	WordUp
79.31	اسپانیایی	Close Track (Contextual)	MultiAztertest
73.43	اسپانیایی	Close Track (Contextual)	BASELINE
73.17	اسپانیایی	Close Track (Contextual)	SQYQP
80.92	باسکی	Close Track (Contextual)	WordUp
76.53	باسکی	Close Track (Contextual)	BASELINE
74.10	باسکی	Close Track (Contextual)	MultiAztertest
67.38	باسکی	Close Track (Contextual)	SQYQP
89.47	اسپانیایی	Open Track	WordUp
77.21	باسکی	Open Track	WordUp
67.08	اسپانیایی	Zero-Shot Track	WordUp
66.30	باسکی	Zero-Shot Track	WordUp

Will-They-Won't-They : WT-WT [13]

The total number of tweets is: **51,284** .

Encoder	Macro F_1 across healthcare opertations: CVS_AET	CI_ESRX	ANTM_CI	AET_HUM	$avgF_1$	avg_wF_1	Average per-class accuracy: *sup*	*ref*	*com*	*unr*
SVM	51.0	51.0	65.7	65.0	58.1	58.5	54.5	43.9	41.2	**88.4**
MLP	46.5	46.6	57.6	59.7	52.6	52.7	55.7	40.3	48.6	68.1
EmbAvg	50.4	51.9	50.4	58.9	52.9	52.3	55.2	50.5	52.7	67.4
CharCNN	49.6	48.3	65.6	60.9	56.1	56.8	55.5	44.2	41.6	82.1
WordCNN	46.3	39.5	56.8	59.4	50.5	51.7	62.9	37.0	31.0	71.7
BiCE	56.5	52.5	64.9	63.0	59.2	60.1	61.0	48.7	45.1	79.9
CrossNet	**59.1**	54.5	65.1	62.3	60.2	61.1	63.8	48.9	50.5	75.8
SiamNet	58.3	54.4	**68.7**	**67.7**	**62.2**	**63.1**	67.0	48.0	52.5	78.3
CoMatchAtt	54.7	43.8	50.8	50.6	49.9	51.6	**71.9**	24.4	33.7	65.9
TAN	56.0	55.9	66.2	66.7	61.2	61.3	66.1	49.0	51.7	74.1
HAN	56.4	**57.3**	66.0	67.3	61.7	61.7	67.6	**52.0**	**55.2**	69.1
mean	53.1	50.5	61.6	62.0	–	–	61.9	44.2	45.8	74.6
upperbound	75.3	71.2	74.4	73.7	74.7	75.2	80.5	89.6	71.8	84.0

Label	Healthcare: CVS_AET # samples	CVS_AET %	CI_ESRX # samples	CI_ESRX %	ANTM_CI # samples	ANTM_CI %	AET_HUM # samples	AET_HUM %	Entertainment: DIS_FOXA # samples	DIS_FOXA %
support	2,469	21.24	773	30.58	970	8.78	1,038	13.14	1,413	7.76
refute	518	4.45	253	10.01	1,969	17.82	1,106	14.00	378	2.07
comment	5,520	47.49	947	37.47	3,098	28.05	2,804	35.50	8,495	46.69
unrelated	3,115	26.80	554	21.92	5,007	45.33	2,949	37.34	7,908	43.46
total	11,622		2,527		11,622		7,897		18,194	

Results on the healthcare operations in the WT–WT dataset.

X-Stance Dataset [14]

It contains 67 000 comments on more than 150 political issues (targets).

Dataset	Evaluation	Score
SemEval-2016	Ghosh et al. (2019)	75.1
MPCHI	Ghosh et al. (2019)	75.6
X-stance	this paper	76.6

	Supervised	Cross-Lingual	Cross-Question	Cross-Topic
M-BERT	**76.6**	70.2	68.4	**69.9**
— with English questions	76.1	**71.7**	**68.5**	69.4
— with missing questions	73.2	67.1	67.8	69.3
— with missing comments	64.2	60.5	51.1	48.6
— with random questions	56.0	52.5	47.7	48.5
— with random comments	50.7	50.7	48.2	48.7
— with target embeddings	70.1	66.0	68.4	69.0

Results for additional experiments. The cross-lingual score is the F1-score on the Italian test set. For the supervised, cross-question and cross-topic settings we report the harmonic mean of the German and French scores.

P-Stance Dataset [15]

The total number of tweets is: **21,574.**

		Trump	Biden	Sanders
Train	Favor	2,937	2,552	2,858
	Against	3,425	3,254	2,198
Val	Favor	365	328	350
	Against	430	417	284
Test	Favor	361	337	343
	Against	435	408	292
Total		7,953	7,296	6,325

Distribution of instances in the P-Stance dataset.

Target: Donald Trump **Stance:** Favor
Document: All Republican presidents are better!
Background knowledge required: Donald Trump was a Republican president.

Target: LeBron **Stance:** Favor
Document: James is a successful basketball player.
Background knowledge required: "LeBron" and "James" refer to the same person.

VAST [16]

Topic: immigration **Stance:** against

Text: The jury's verdict will ensure that another violent criminal alien will be removed from our community for a very long period . . .

	Train	Dev	Test
# Examples	13477	2062	3006
# Unique Comments	1845	682	786
# Few-shot Topics	638	114	159
# Zero-shot Topics	4003	383	600

Data split statistics for VAST.

	F1 All			F1 Zero-Shot			F1 Few-Shot		
	pro	con	all	pro	con	all	pro	con	all
CMaj	.382	.441	.274	.389	.469	.286	.375	.413	.263
BoWV	.457	.402	.372	.429	.409	.349	.486	.395	.393
C-FFNN	.410	.434	.300	.408	.463	.417	.413	.405	.282
BiCond	.469	.470	.415	.446	.474	.428	.489	.466	.400
Cross-Net	.486	.471	.455	.462	.434	.434	.508	.505	.474
BERT-sep	.4734	.522	.5014	.414	.506	.454	.524	.539	.544
BERT-joint	.545	**.591**	.653	.546	.584	.661	.544	**.597**	.646
TGA Net	**.573***	.590	**.665**	**.554**	**.585**	**.666**	**.589***	.595	**.663**

Persian Stance Classification Dataset [4]

news	2124
Rumored claims	534

Source	Claim Count	Headline as Claim	Modified Headline as Claim	Headline as Claim Percentage
Shayeaat	513	513	0	100%
Fakenews	87	37	50	42.52%

The distribution of unchanged vs updated claims in the dataset.

Agreement time	Headline-claim	Article-claim	Article-Headline	Claims veracity
Before adjudication	82.15%	80.01%	81.49%	92.25%
After rechecking	93.21%	92.01%	92.49%	96.25%
After majority vote	98.05%	97.50%	98.49%	99.60%

Label agreement percentage at different stages of data validation.

Type	Agree	Discuss	Disagree	Unrelated
article-claim stance	7.43%	54.85%	11.16%	28.53%
headline-claim stance	20.17%	39.75%	8.08%	31.98%
article-headline stance	29.24%	63.51%	6.56%	0.64%

Class distribution of article-claim stance, headline-claim stance and article-headline stance.

Claim:
Kamal Kharrazi meeting with John Kerry in Paris
ملاقات کمال خرازی با جان کری در پاریس

Headline:
Kamal Kharrazi encounters with John Kerry in Paris
دیدار کمال خرازی و جان کری در پاریس
Stance: Agree

Headline:
The visit of Kamal Kharrazi to John Kerry was denied
تکذیب خبر دیدار کمال خرازی با جان کری
Stance: Discuss

Headline:
The news of Kharrazi meeting with John Kerry is a big lie
خبر دیدار خرازی با کری دروغ محض است
Stance: Disagree

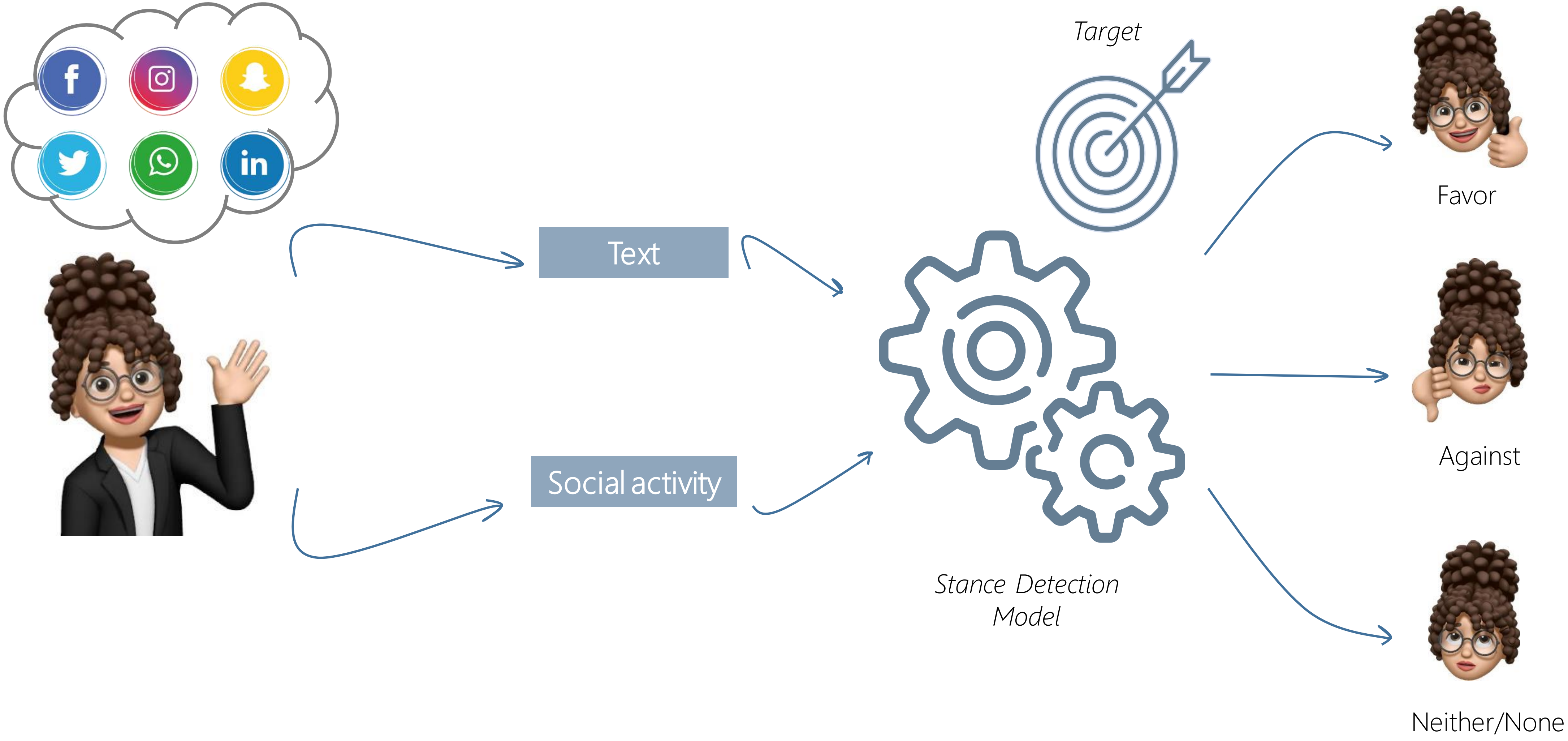
Headline:
Kamal Kharrazi said that Iran seeks peace and stability in the region
کمال خرازی عنوان کرد که ایران به دنبال صلح و آرامش در منطقه است
Stance: Unrelated

Veracity: False

Methods of Stance Detection

- Machine learning based on feature
- Deep learning
- Pre-trained models

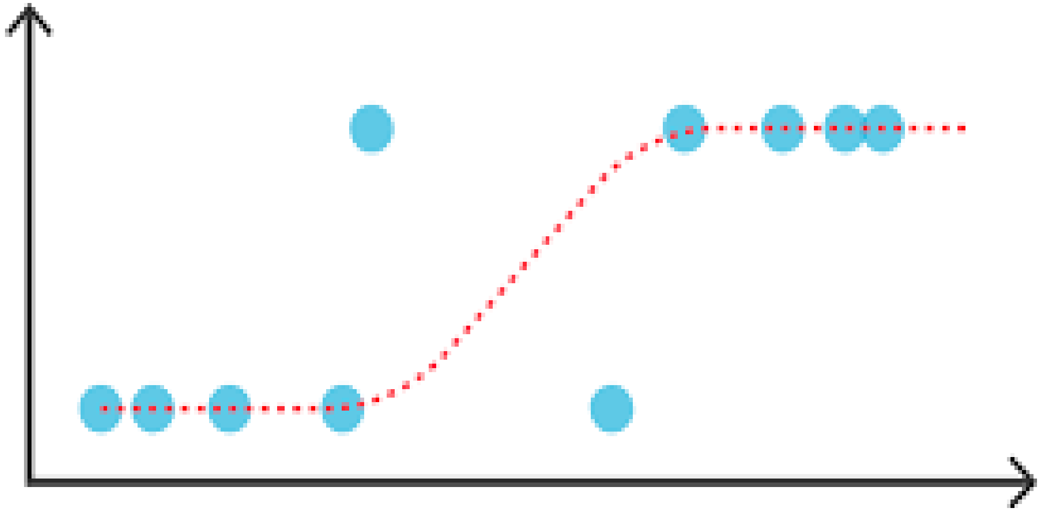
Features Used



Machine Learning Based On Feature Approach

Logistic Regression

word representation vector, similarity between words, Text sentiment and tweet-specific features as input to the model.



SVM

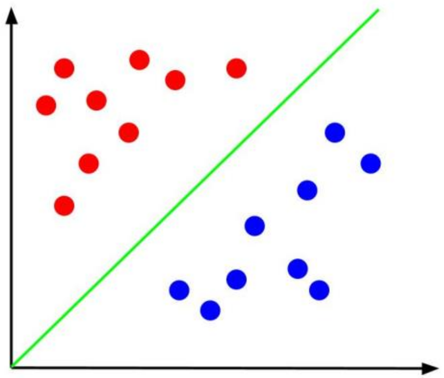
SemEval2016 : F-score: 68.96 [8]

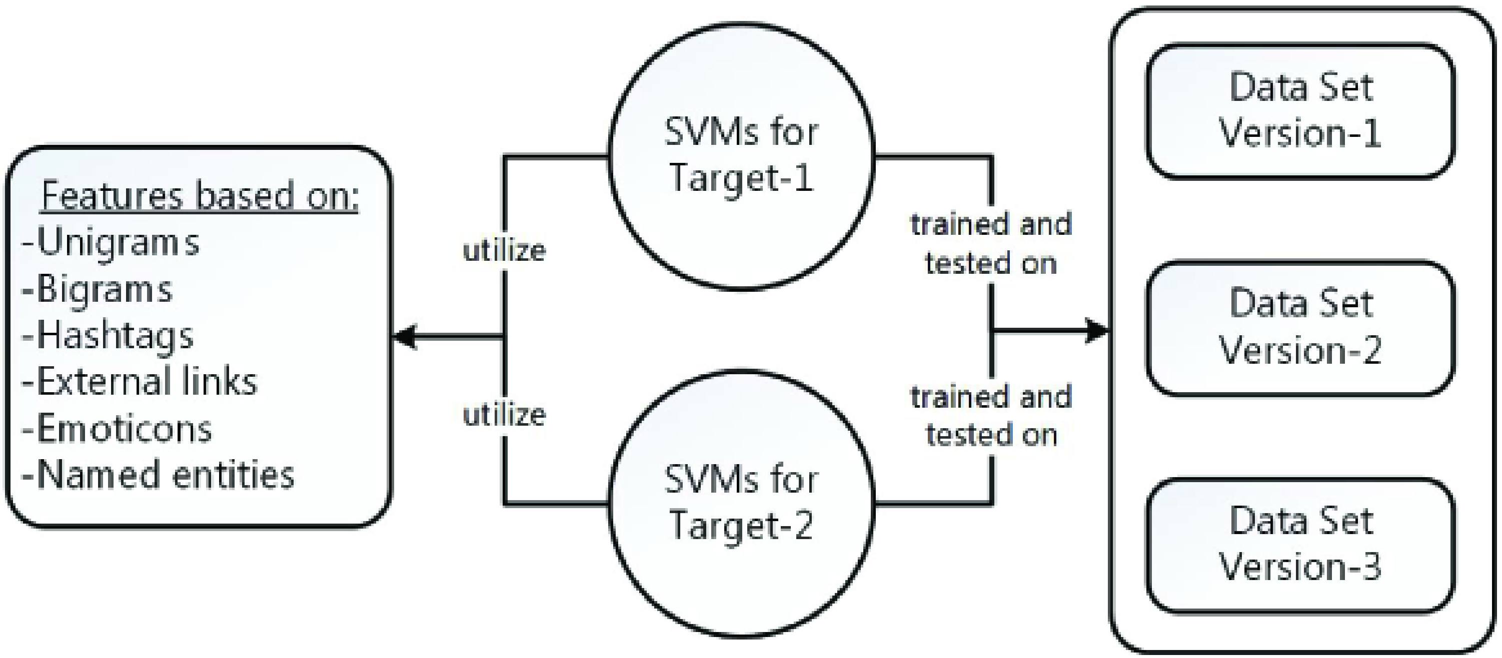
TakeLab : F-score: 66.83 [2]

JU_NLP : F-score: 60.60 [17]

INF-UFRGS : F-score: 42.32 [18]

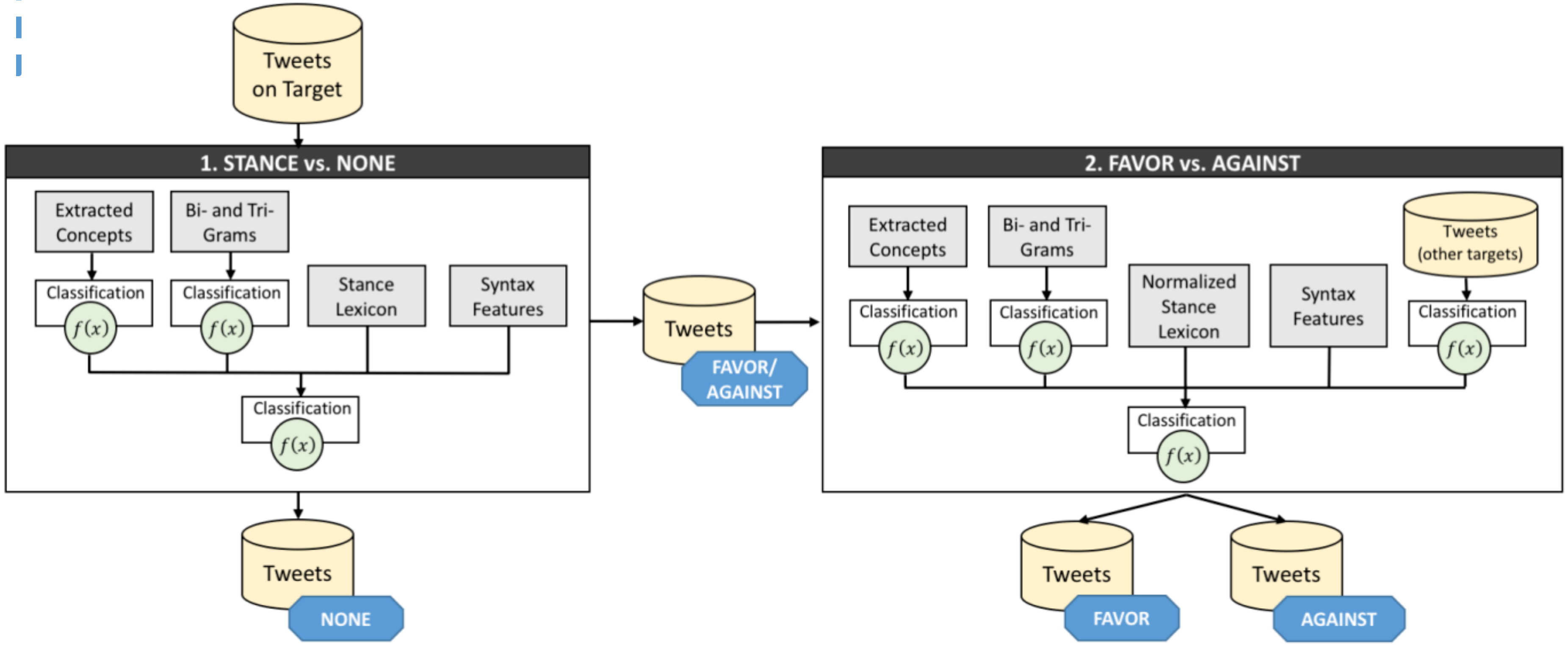
CU-GWU : F-score: 63.60 [19]





Stacked Classifier [20]

F-score : 61.73

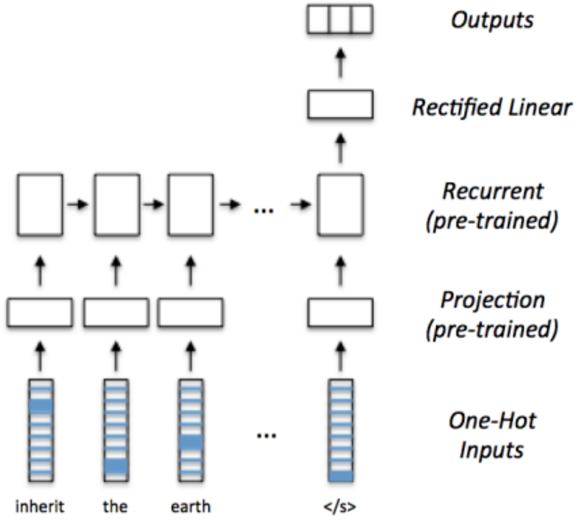


Deep Learning Approach

LSTM

MITRE [21]

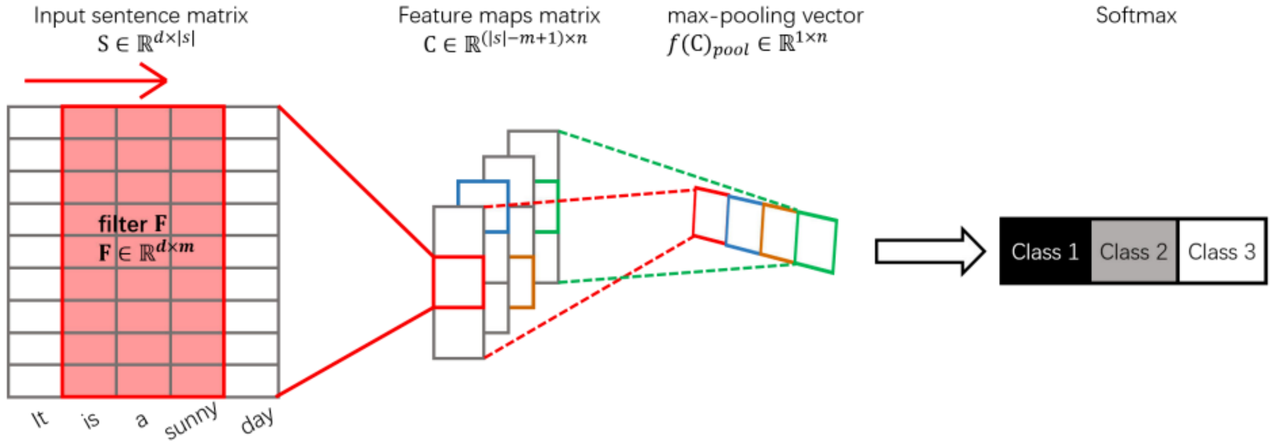
F-score : 67.82



CNN

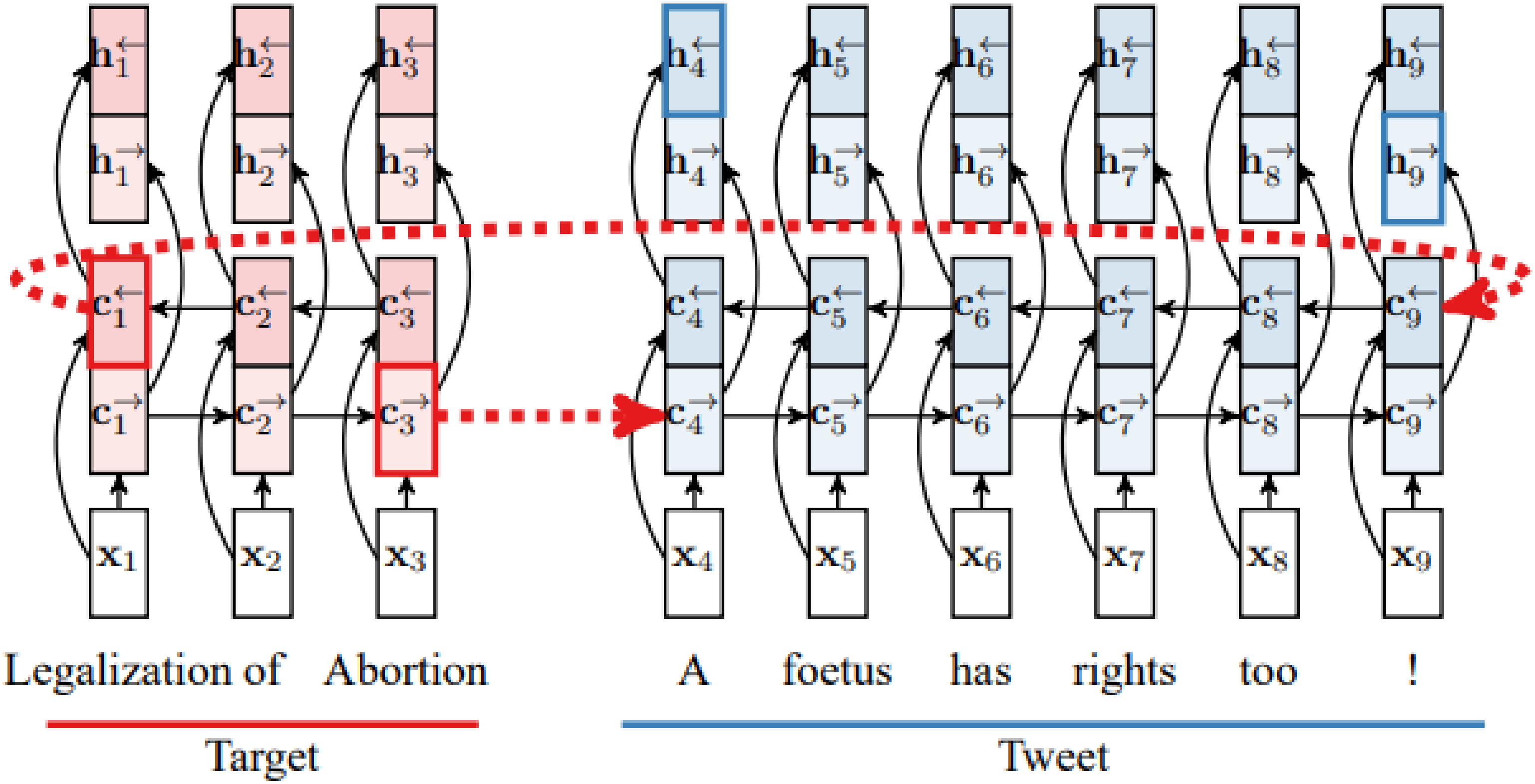
Pkudblab[22]

F-score : 67.82



BiLSTM

- First BiLSTM is responsible for generating a representation of 44 subjects.
- Second BiLSTM is also a representation of the tweet text
- Used conditional model.



BiCond Architecture[23]

Tan [24]

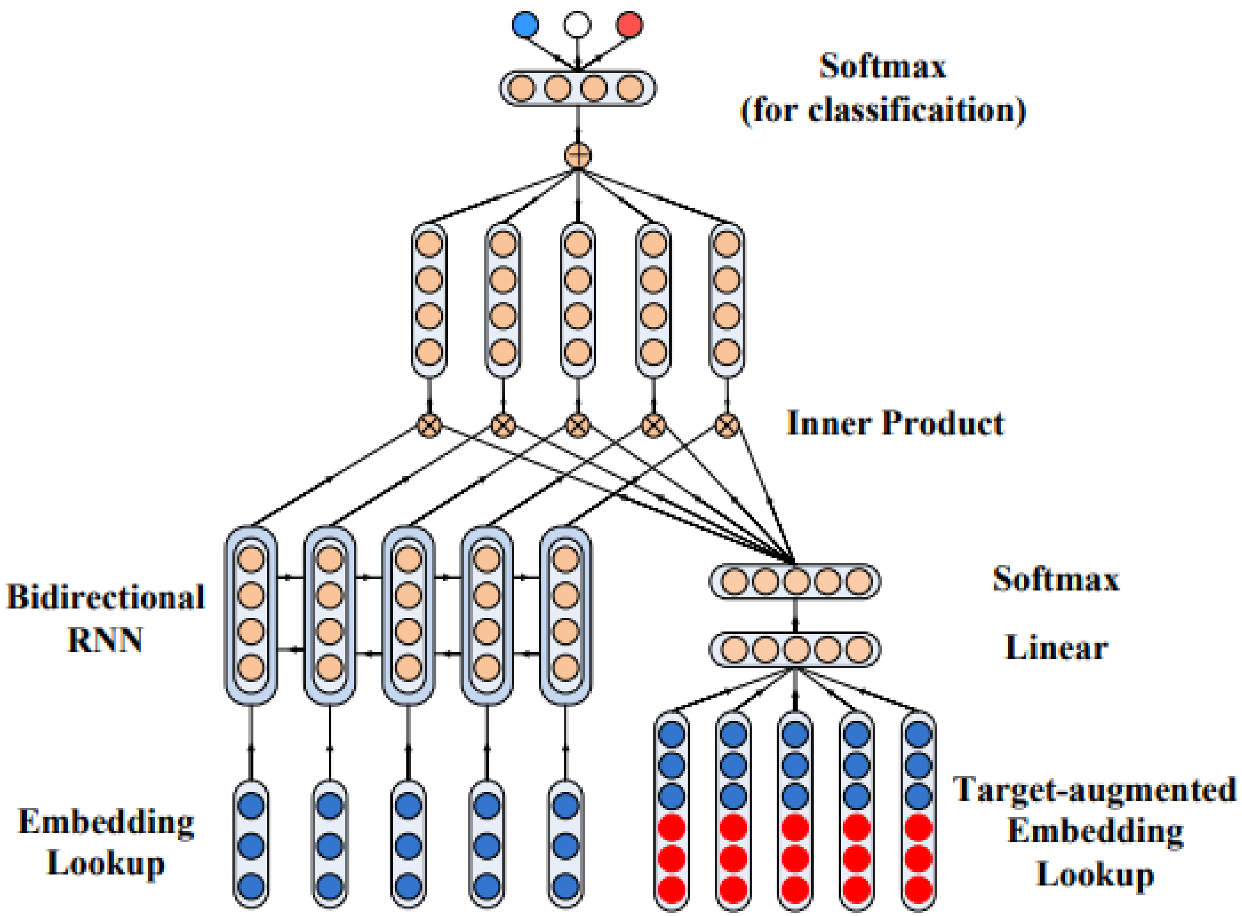
- Mechanism of attention
- Used BiLSTM model

F-score : 68.79

Target: Atheism Stance: Favor Sentiment: Negative

Religion has destroyed the ability for some to say know

Predicted Results:
TAN : Favor
Standard LSTM: Against



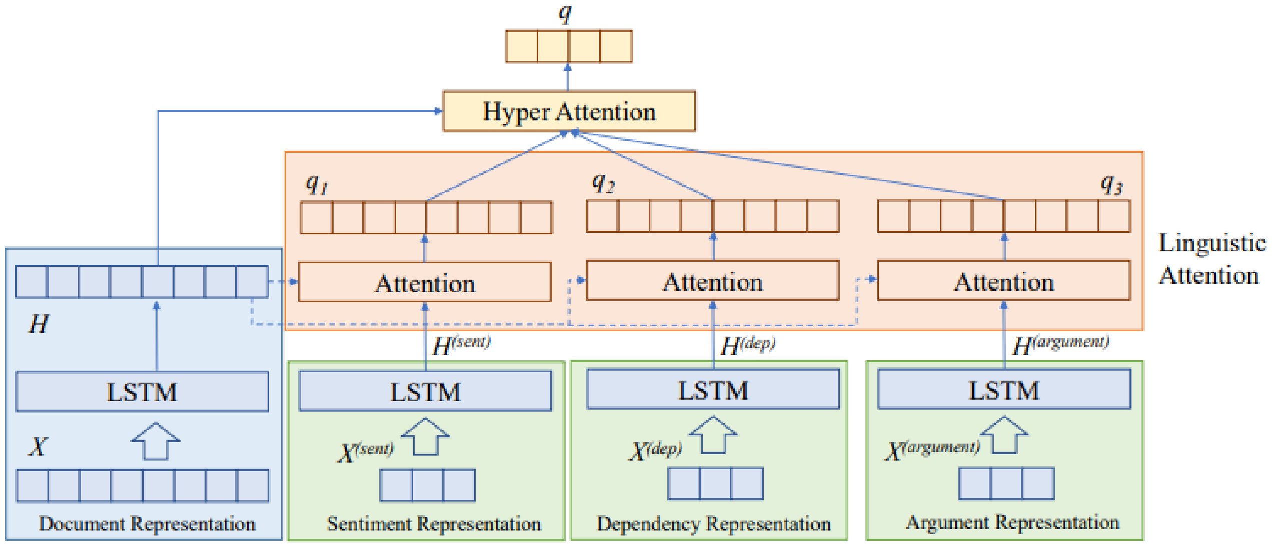
Overall Architecture of TAN.

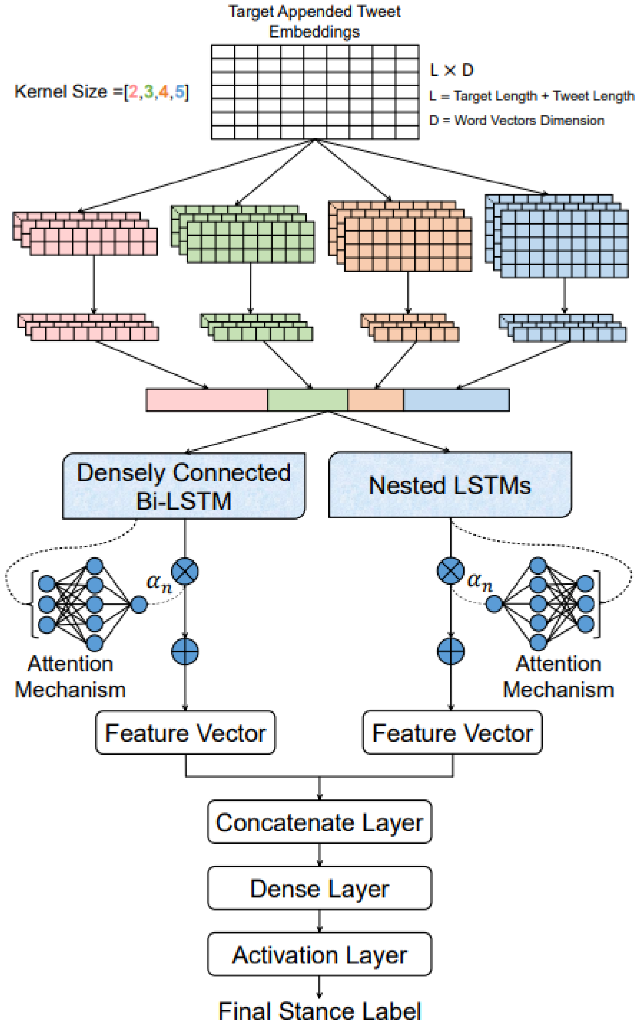
Han[25]

F-score : 70.53

PNEM[26]

F-score : 72.11





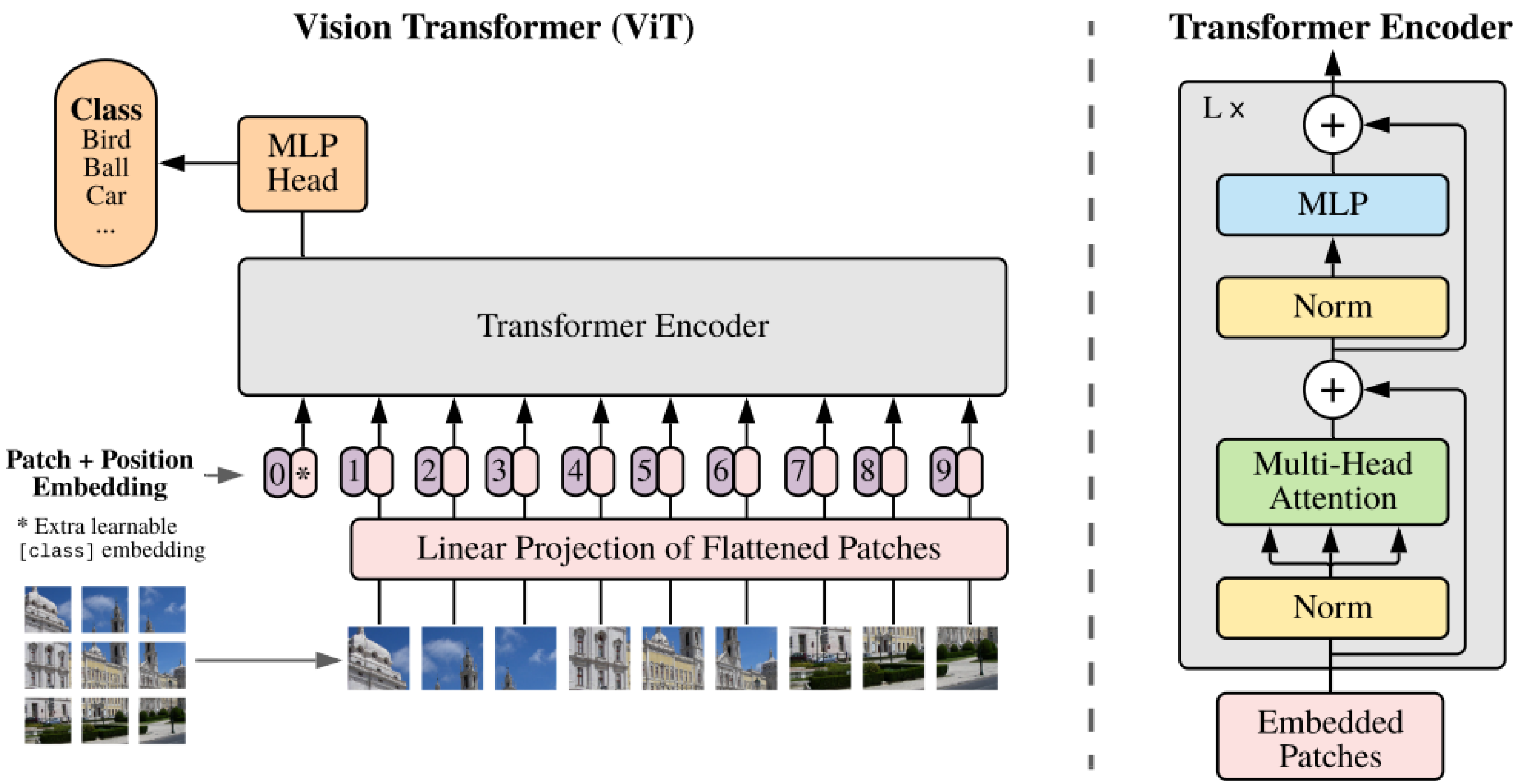
An Overview On Methods Of Stance Detection

Best models :

- PNEM
- HAN
- TAN

F_{avg}	Dataset	Approach	year	Models
72.11	SemEval2016 (A)	Nested LSTMs	2019	PNEM
70.53	SemEval2016 (A)	Hierarchical Attention NN	2018	Han
69.42	SemEval2016 (A)	Bi-directional GRU-CNN	2017	AS-biGRU-CNN
68.79	SemEval2016 (A)	BiLSTM	2017	Tan
72.88	NLPCC-ICCPOL-2016 Chinese Dataset	BiLSTM	2017	Tan
67.82	SemEval2016 (A)	LSTM	2016	MITRE
67.33	SemEval2016 (A)	CNN	2016	pkudblab
66.83	SemEval2016 (A)	SVM, Random Forest	2016	TakeLab
63.42	SemEval2016 (A)	Maximum Entropy Classifier	2016	UWB
42.02	SemEval2016 (B)	Maximum Entropy Classifier	2016	UWB
42.32	SemEval2016 (B)	SVM	2016	INF-UFRGS
63.60	SemEval2016 (A)	SVM	2016	CU-GWU
63.54	SemEval2016 (A)	CNN	2016	DeepStance
61.73	SemEval2016 (A)	stacked classifier (SVM)	2016	tl.uni-due
60.60	SemEval2016 (A)	SVM	2016	JU NLP
58.90	SemEval2016 (A)	Logistic Regression and CNN	2016	Tohoku

Pre-trained models



TweetEval [27]

Used **RoBERTa** model

Task	Lab	Train	Val	Test
Emoji prediction	20	45,000	5,000	50,000
Emotion det.	4	3257	374	1421
Hate speech det.	2	9,000	1,000	2,970
Irony detection	2	2,862	955	784
Offensive lg. id.	2	11,916	1,324	860
Sent. analysis	3	45,389	2,000	11,906
Stance detection	3	2620	294	1249
Stance/Abortion	3	587	66	280
Stance/Atheism	3	461	52	220
Stance/Climate	3	355	40	169
Stance/Feminism	3	597	67	285
Stance/H. Clinton	3	620	69	295

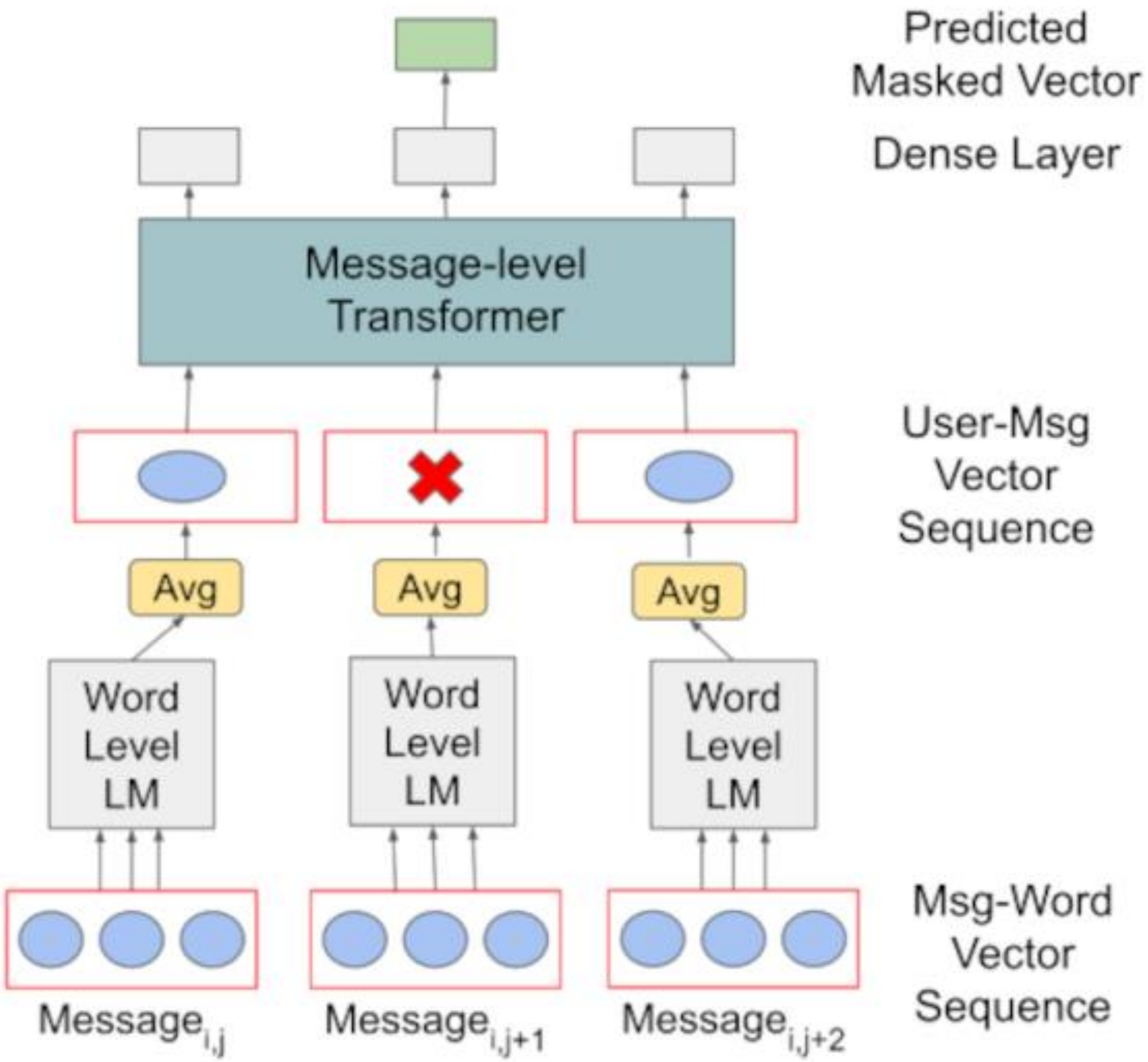
		Emoji	Emotion	Hate	Irony	Offensive	Sentiment	Stance	ALL
Val	SVM	25.0	63.8	73.1	63.4	72.7	68.4	67.9	62.0
	FastText	23.2	62.9	71.7	62.7	70.0	62.2	67.3	60.0
	BLSTM	19.4	62.6	72.1	60.6	72.1	61.9	63.4	58.9
	RoB-Bs	24.7±0.3 (24.3)	73.1±1.7 (74.9)	76.5±0.3 (76.6)	73.7±0.6 (73.7)	77.1±0.6 (77.6)	71.4±1.9 (72.7)	71.4±1.9 (73.9)	67.7
	RoB-RT	24.4±1.5 (**26.2**)	75.4±1.5 (**77.0**)	77.8±1.1 (**79.6**)	74.7±1.5 (**75.6**)	77.2±0.6 (**77.7**)	73.0±1.2 (**74.2**)	72.9±1.0 (**75.2**)	**69.4**
	RoB-Tw	23.4±1.1 (24.6)	67.6±0.9 (68.6)	74.3±2.0 (76.6)	70.0±0.3 (70.7)	76.1±0.6 (76.2)	70.5±1.0 (69.4)	68.3±2.4 (71.4)	65.4
Test	SVM	29.3	64.7	36.7	61.7	52.3	62.9	67.3	53.5
	FastText	25.8	65.2	50.6	63.1	73.4	62.9	65.4	58.1
	BLSTM	24.7	66.0	52.6	62.8	71.7	58.3	59.4	56.5
	RoB-Bs	30.9±0.2 (30.8)	76.1±0.5 (76.6)	46.6±2.5 (44.9)	59.7±5.0 (55.2)	79.5±0.7 (78.7)	71.3±1.1 (72.0)	68±0.8 (70.9)	61.3
	RoB-RT	31.4±0.4 (**31.6**)	78.5±1.2 (**79.8**)	52.3±0.2 (**55.5**)	61.7±0.6 (62.5)	80.5±1.4 (**81.6**)	72.6±0.4 (**72.9**)	69.3±1.1 (**72.6**)	**65.2**
	RoB-Tw	29.3±0.4 (29.5)	72.0±0.9 (71.7)	46.9±2.9 (45.1)	65.4±3.1 (**65.1**)	77.1±1.3 (78.6)	69.1±1.2 (69.3)	66.7±1.0 (67.9)	61.0
	Best	36.0*	-	65.1	70.5	82.9	68.5	71.0	-
Metric		M-F1	M-F1	M-F1	$F^{(i)}$	M-F1	M-Rec	AVG ($F^{(a)}$, $F^{(f)}$)	TE

MeLT [28]

Only by checking the user's message, it is not possible to determine the position of the message in relation to a specific topic.

Used the last forty messages.

F-score : 73



F-measure

$$F_{Favor} = \frac{2P_{Favor}R_{Favor}}{P_{Favor} + R_{Favor}}$$

$$F_{Against} = \frac{2P_{Against}R_{Against}}{P_{Against} + R_{Against}}$$

$$F_{average} = \frac{F_{Favor} + F_{Against}}{2}$$

Precision

$$P_{Favor} = \frac{Correct_{Favor}}{Correct_{Favor} + Missing_{Favor}}$$

$$P_{Against} = \frac{Correct_{Against}}{Correct_{Against} + Missing_{Against}}$$

Recall

$$R_{Favor} = \frac{Correct_{Favor}}{Correct_{Favor} + Spurious_{Favor}}$$

$$R_{Against} = \frac{Correct_{Against}}{Correct_{Against} + Spurious_{Against}}$$

Persian Stance Classification Dataset

First Stance Detection Dataset In Persian

Persian Stance Classification Dataset

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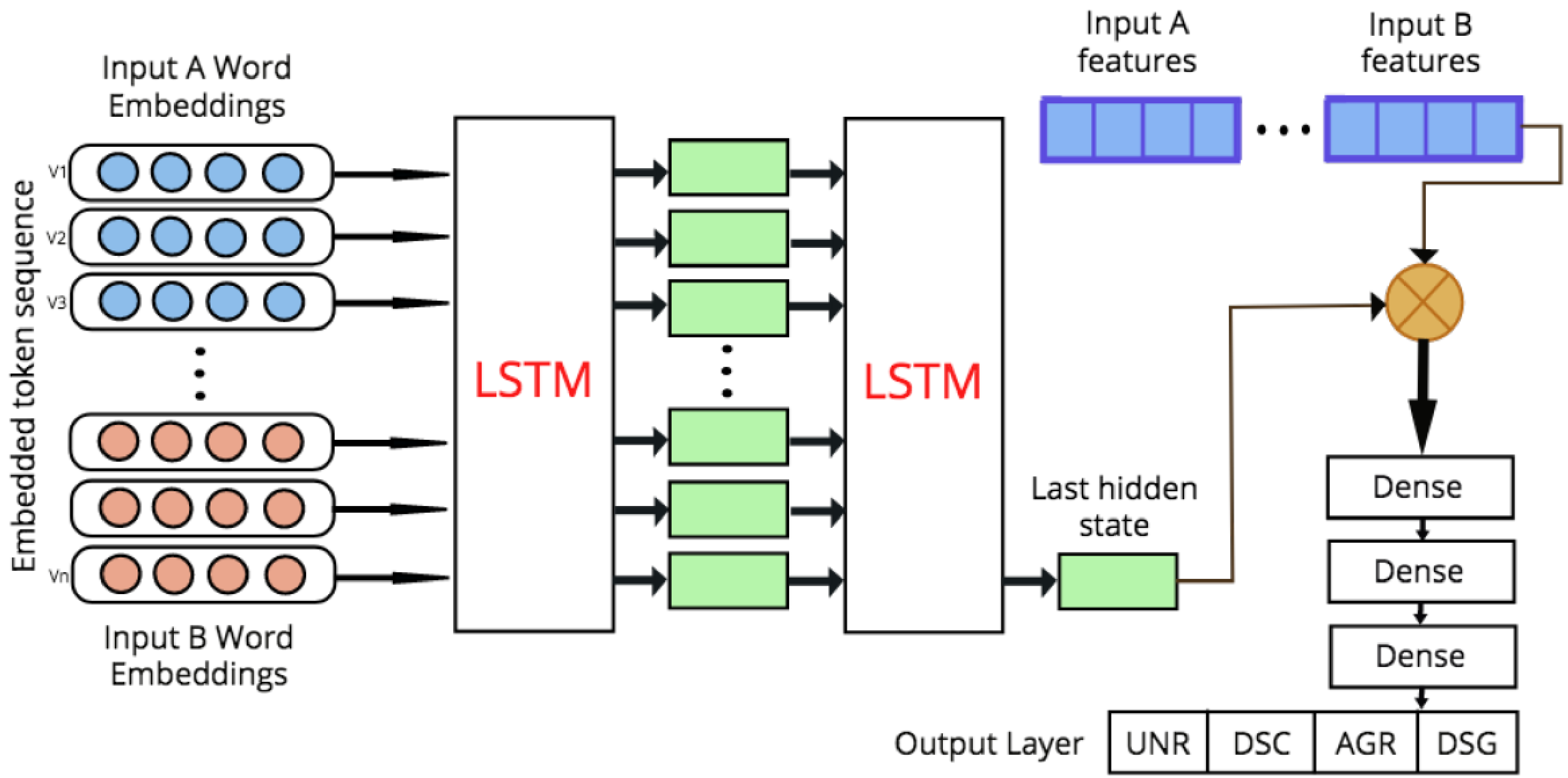
Abstract

We present the first stance detection dataset in Persian which has applications in fact-checking and summarization (Ferreira and Vlachos, 2016). We developed a web-based tool for importing rumored claims, collecting associated news-articles and labeling their stance against the claims. We used this tool to label 2,124 news articles against 534 rumored claims. We provide a number of baseline classification methods based on Ferreira and Vlachos (2016). In addition we introduce language specific features that outperform all baseline systems on this dataset.

focus on stance detection for Twitter data. Thorne et al. (2018) provide a fact extraction dataset that uses facts extracted from Wikipedia to generate factual and false claims. In 'Liar, Liar Pants on Fire', Wang (2017) provides a dataset extracted from `PolitiFact`[1]. The aforementioned works are all in English.

In absence of any fake news dataset for Persian, we collect claims from `Fakenews`[2] and `Shayeaat`[3] websites. Then we look for articles related to claims. After collecting articles, for each claim we allocate three labels; first label is article (body text) stance according to the claim (article-claim stance), second label is

StackLSTM [4]



Input A Word Embeddings
Embedded token sequence
V1
V2
V3
Vn
Input B Word Embeddings
LSTM
LSTM
Input A features
Input B features
Last hidden state
Dense
Dense
Dense
Output Layer
UNR
DSC
AGR
DSG

Evaluation Metrics in StackLSTM

	Features based on Bag-of-words				Features based on TF-IDF			
Models	**pre.**	**Recall**	**F1**	**acc.**	**pre.**	**Recall**	**F1**	**acc.**
Random Forest	0.70	0.69	0.67	**0.69**	0.69	0.68	0.68	**0.68**
Logistic Regression	0.63	0.63	0.63	0.63	0.63	0.64	0.63	0.64
SVM	0.64	0.63	0.63	0.63	0.64	0.64	0.64	0.64
Naive Bayes	0.50	0.50	0.50	0.50	0.60	0.49	0.49	0.49
Majority	0.15	0.39	0.22	0.39	0.15	0.39	0.22	0.39
stackLSTM	0.63	0.62	0.62	0.62	–	–	–	–

Headline-claim stance classification

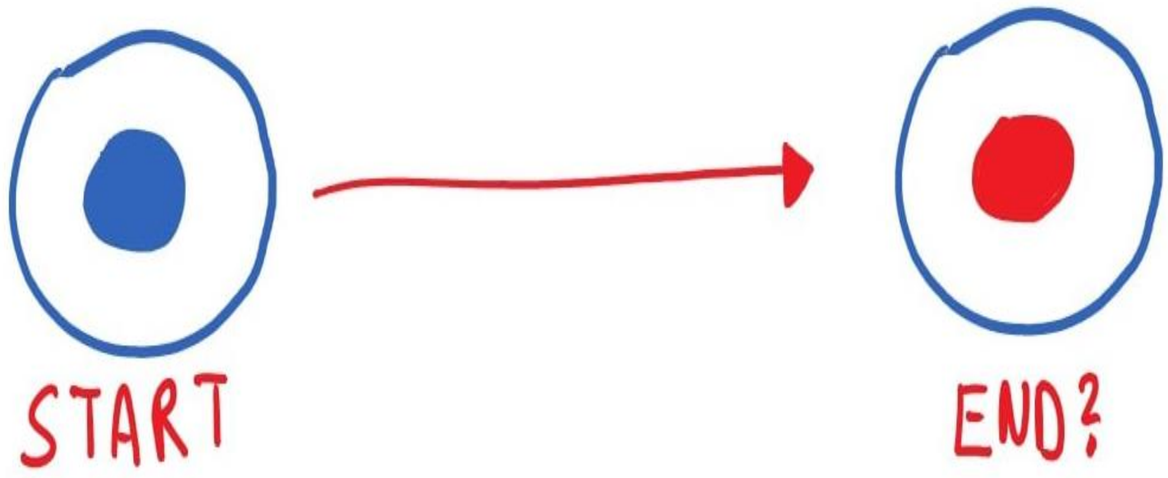
Article-claim stance classification

	Features based on Bag-of-words				Features based on TF-IDF			
Models	**pre.**	**Recall**	**F1**	**acc.**	**pre.**	**Recall**	**F1**	**acc.**
SVM	0.55	0.56	0.55	0.565	0.59	0.61	0.58	**0.610**
Logistic Regression	0.57	0.59	0.57	0.592	0.59	0.60	0.54	0.597
Random Forest	0.52	0.57	0.49	0.575	0.58	0.60	0.55	0.605
Naive Bayes	0.50	0.58	0.52	0.580	0.57	0.57	0.51	0.575
Majority	0.27	0.52	0.36	0.522	0.27	0.52	0.36	0.522
stackLSTM	0.57	0.62	0.71	**0.72**	–	–	–	–

BERT

TRANSFORMER

Conclusion



Future Work

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THANKS!

Any questions?

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