OPINION MINING IN SOCIAL MEDIA

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WHAT WAS THE PROJECT GOAL?

Classifying social media posts as objective and subjective

SUBJECTIVTY

- Text contains sentiment, feeling, opinion
- Questions accepts more than one answer

OBJECTIVITY

- Text contains only facts
- Questions with only one answer

DATASET

SOURCE

Tweets from Twitter

DOMAINS

In-Domain
[james bond, restaurants, fifa]
Objective: 433 | Subjective: 411

Out-Domain
[movies, squid game]
Objective: 204 | subjective: 466

COLLECTING METHOD

Tool : Twint
Manual labeling

LABELING

Krippendorff´s Alpha Score: 83.1 – 92.8 %

ReCal 0.1 Alpha for 2 Coders
results for file "kAlphaNumbers.csv"

File size:	3470 bytes
N columns:	2
N variables:	1
N coders per variable:	2

	Percent Agreement	Scott's Pi	Cohen's Kappa	Krippendorff's Alpha (nominal)	N Agreements	N Disagreements	N Cases	N Decisions
Variable 1 (cols 1 & 2)	92.8%	0.8	0.801	0.8	644	50	694	1388

UDE

MACHINE LEARNING

01 RAW DATASET

02 TEXT PREPROCESSING
Keep punctuations

03 TRANSLATE EMOJIS

04 LOOK FOR QUESTION MARKS

05 REMOVE PUNCTUATIONS

06 COUNT WORDS

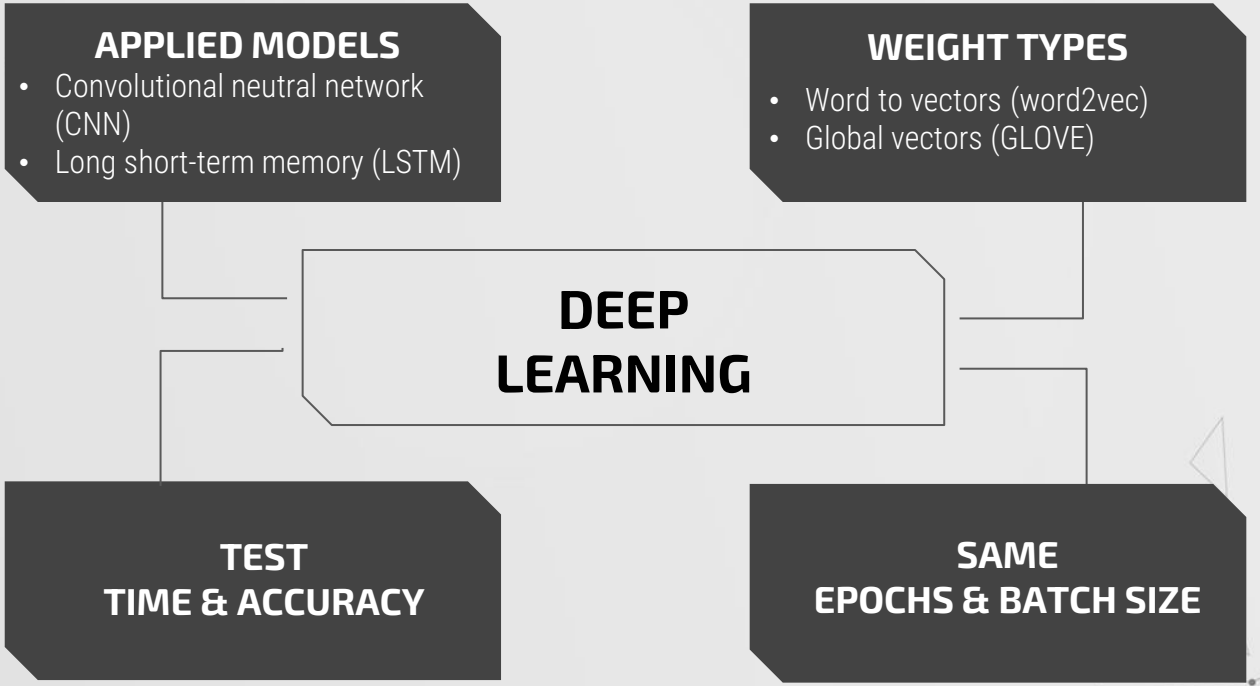
07 TF-IDF VECTORISING

08 START PREDICTING SDG/SVM

09 VALIDATE MODEL

ML RESULTS

	Target	Precision	Recall	F1-Score
In-Domain	Objective Subjective	42% 93%	72% 78%	53% 85%
Out-Domain	Objective Subjective	47% 77%	47% 77%	47% 77%


APPLIED MODELS
• Convolutional neutral network (CNN)
• Long short-term memory (LSTM)
WEIGHT TYPES
• Word to vectors (word2vec)
• Global vectors (GLOVE)
DEEP LEARNING
TEST TIME & ACCURACY
SAME EPOCHS & BATCH SIZE

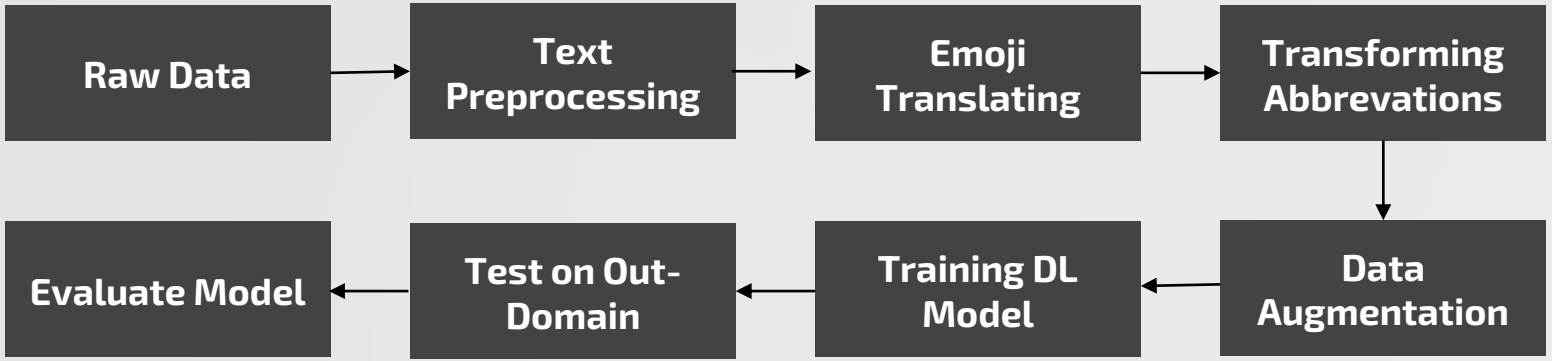
In-Domain

	CNN		LSTM	
	Word2Vec	GLOVE	Word2Vec	GLOVE
Time	1 min 28 sec	1 min 42 sec	46 min 4 sec	7 min 18 sec
Objectivity				
Precision	81%	98%	92%	98%
Recall	94%	84%	95%	99%
F1-Score	87%	90%	94%	98%
Subjectivity				
Precision	95%	80%	95%	99%
Recall	83%	97%	92%	98%
F1-Score	88%	88%	94%	98%

Out-Domain

	CNN		LSTM	
	Word2Vec	GLOVE	Word2Vec	GLOVE
Time	1 min 28 sec	1 min 42 sec	46 min 4 sec	7 min 18 sec
Objectivity				
Precision	25%	71%	54%	51%
Recall	34%	45%	37%	51%
F1-Score	29%	55%	44%	51%
Subjectivity				
Precision	79%	63%	60%	79%
Recall	71%	83%	75%	79%
F1-Score	75%	72%	67%	79%

MODEL ARCHITECTURE



Tackle Overfitting:

- add more entries ✓
- back-translation ✓
- dropout layers ✓
- shuffle text ✗

CNN + GLOVE

IN-DOMAIN

Target	Precision	Recall	F1-Score
Objective	97%	90%	93%
Subjective	89%	97%	93%

OUT-DOMAIN

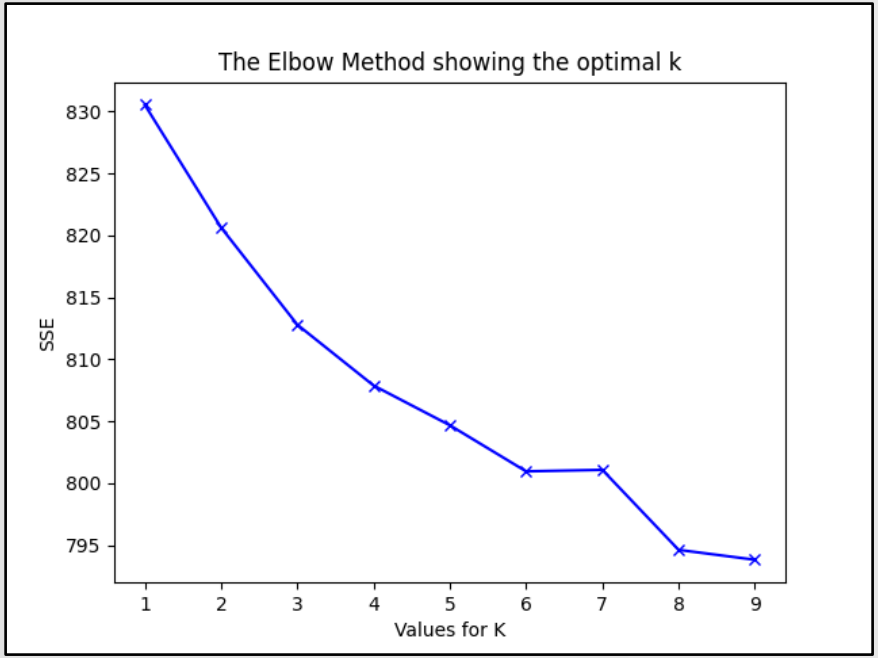
Target	Precision	Recall	F1-Score
Objective	63%	57%	60%
Subjective	79%	83%	81%

THE BEST MODEL

CLUSTERING

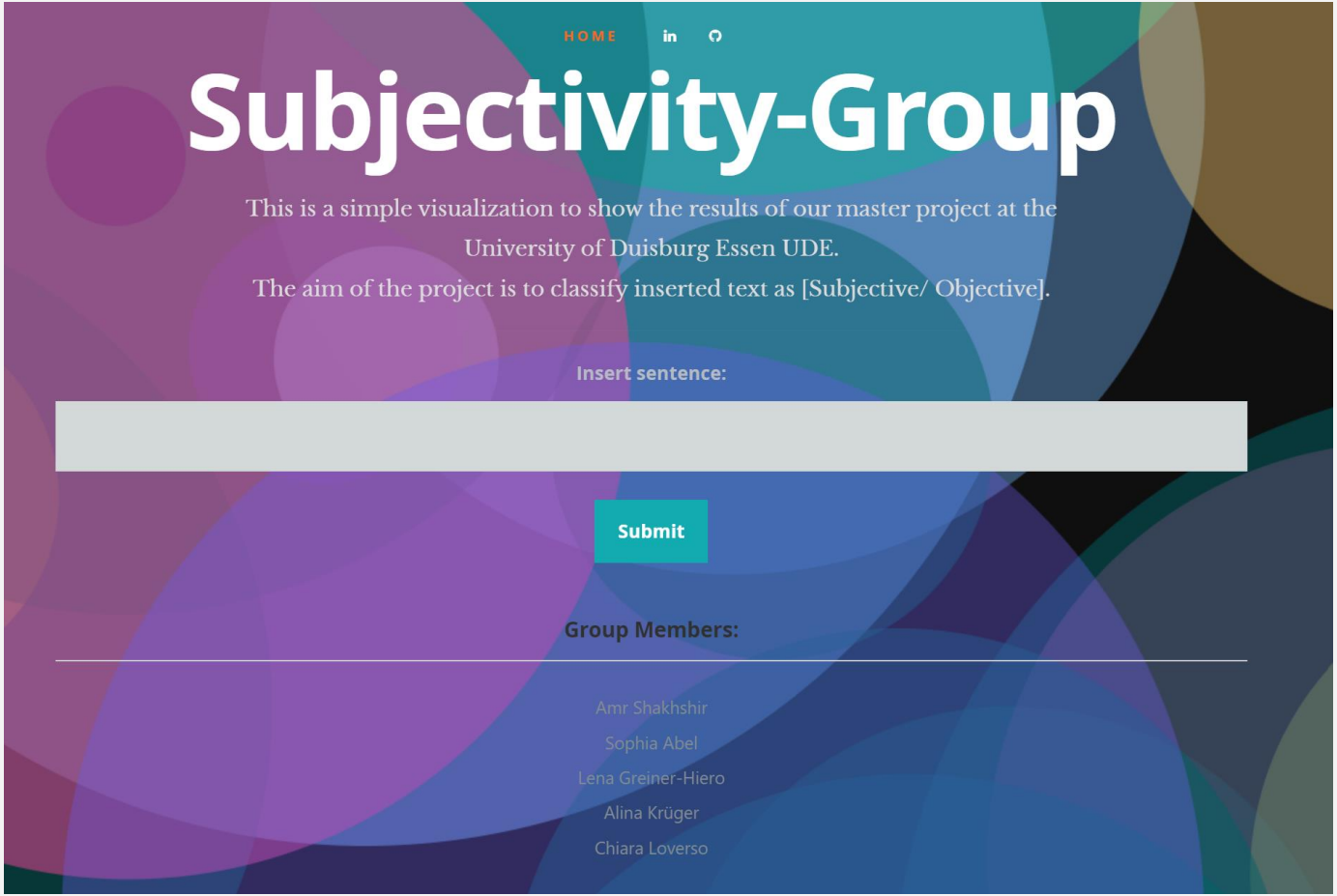
K-means:
- 8 clusters
- Evaluation-Score: 0.016

DBSCAN:
- 5 clusters
- Evaluation-Score: 0.014



Cluster 0:	**Cluster 1:**
yes	bond
new	ive
lol	ryan
7910	movie
098	canadian
077	saying
covid	playing
mean	bean
dont	
man	

LIVE DEMO


HOME
Subjectivity-Group
This is a simple visualization to show the results of our master project at the University of Duisburg Essen UDE.
The aim of the project is to classify inserted text as [Subjective/ Objective].
Insert sentence:
Submit
Group Members:
Amr Shakhshir
Sophia Abel
Lena Greiner-Hiero
Alina Krüger
Chiara Loverso

OBTAINED SKILLS

Skills	Alina		Amr		Chiara		Lena		Sophia	
	Proficiency	Relevancy	Proficiency	Relevancy	Proficiency	Relevancy	Proficiency	Relevancy	Proficiency	Relevancy
ML basic concepts	1	0	3	1	1	0	1	0	1	0
Text preprocessing	2	0	3	1	2	0	2	0	2	0
Deep learning concepts	0	0	2	1	0	0	0	0	0	0
Categorizing entries	3	1	1	1	3	1	3	1	3	1
Working in a group	3	1	3	1	3	1	3	1	3	1
Managing the group	3	1	3	1	3	1	3	1	3	1
Looking for new ideas	2	1	3	1	2	1	2	1	2	1
Explaining own part of task clearly	3	1	3	1	3	1	3	1	3	1
Specifying current & future goal	2	1	3	1	2	1	2	1	2	1
Ability to communicate	3	1	3	1	3	1	3	1	3	1

***Proficiency**
0: No capabilities
1: Basic level
2: Intermediate level
3: Advanced level

***Relevancy**
0: The capability is *not* relevant to the field of study/ task
1: The capability is relevant to the field of study/ task

FURTHER IMPROVEMENTS

- Connect application to a datebase
- Assign text that is inserted by users to the database
- Allow users to rate classification result in order to monitor and improve accuracy
- Add aspect detection model

Sources

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[6] LSTM tutorial: https://towardsdatascience.com/choosing-the-right-hyperparameters-for-a-simple-lstm-using-keras-f8e9ed76f046
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