Natural Language Processing in Digital Humanities: a case study

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Digital humanities & Natural Language processing

Digital humanities→ no commonly accepted definition   (McGillivray, 2020

→ no standard description of the relation with Natural Language Processing (NLP)

⇒ an area that combines computing, digital resources and the traditional disciplines of humanities (Helsinki University, n.d.)

Suitable topics:

- Text analysis and processing related to humanities using computational methods
- Thorough error analysis of an NLP system using (digital) humanities methods
- Dataset creation and curation for NLP (e.g. digitization, digitalization, datafication, and data preservation).
- Research on cultural heritage collections such as national archives and libraries using NLP
- NLP for error detection, correction, normalization and denoising data
- Generation and analysis of literary works such as poetry and novels
- Analysis and detection of text genres (The 2nd International Workshop on Natural Language Processing for Digital Humanities – NLP4DH, 2022).

Like-farming research on Facebook & NLP

Emotional like-farming research on Facebook requires:

-creation and curation of a multimodal dataset

-extensive annotation (manual or not)

-error detection and denoising parced annotation entries

-use of appropriate python methods for a sociolinguistic text analysis & data visualisation

-error analysis on Greek NLP models to revise practices

-error detection to interpret design practises

-NLU methods for sentiment analysis

⇒ identify, interpret emotional exploitation like-farming characteristics

as fake news genre characteristics

What is like-farming?

No relevant research

Like-farming⇒ a little known fake news practice (Daniilidis, 2013)

⇒ part of engagement farming practices (Facebook, 2012)

Different from response farming→ click baits

Like-farming posts→ stand alone **Some**
Like-farming variations

→ spam, scam. fraud -
Emotional exploitation

→ satisfy attention seeking designer -Genius Puzzles

-Facebook competition or giveaways

-Charitable donations …

-Religious/political affinity

-Superstition (Charles, 2016)

Focus on emotional exploitation like-farming

Emotional exploitation like-farming news: fact checking organizations (Hellinika Hoaxes)

⇒ Posts mainly about vulnerable social groups (disabled people, sick children, elderly etc.)

Aim

→ not at provoking social concern and action

→ turning them to objects of exploitation

Emotional like farming layout structure

Multimodal structure:

-Group or Page logo & name

-Time stamp

-Friend tag

-Post text with emojis/emoticons or not

-Central-dominant image

-Superimposed text on image

-Social cues-metrics (like, share, comment number)

-Reposting comment by intermediary

-Comments ⇒ **primary metadata in data set**

Data set formation complexity

Data set structure is not limited in these metadata entries.

The fake news design layer adds complexity in data set structure.

-existing data sets→ primary, secondary and tertiary label tags with mixed criteria

→ mostly monomodal research approach

⇒ little relevance to our multimodal research subject

-data set under construction→ all instances in data set are fact checked by researcher

or debunked by fact checking organizations

References	News Domain	Application area	Type of disinformation	Language
Barbado et al., 2019	Technology	Fake detection	Fake reviews	English
Zubiaga et al., 2016; Giasemidis et al., 2018; Bondielli and Marcelloni, 2019; Alkhodair et al., 2019	Society, politics	Rumour detection	Rumours	English and German
Mitra and Gilbert, 2015; Sowmya and Shankar, 2019; Bondielli and Marcelloni, 2019; Zhang and Ghorbani, 2019	Society	Veracity classification	Rumours	English
Santia and Williams, 2018; Sowmya and Shankar, 2019; Bondielli and Marcelloni, 2019; Reis et al., 2019	Politics, society	Veracity classification	Fake news articles	English
Tacchini et al., 2017; Sowmya and Shankar, 2019; Bondielli and Marcelloni, 2019	Science	Fake detection	Hoaxes	English
Wang, 2018; Bondielli and Marcelloni, 2019; Zhang and Ghorbani, 2019; Aldwairi and Alwahedi, 2018; Torabi and Taboada, 2019	Politics	Fake detection	Fake news articles	English
Vlachos and Riedel, 2014; Bondielli and Marcelloni, 2019	Politics, society	Fact checking	Fake news articles	English
Thorne et al., 2018; Bondielli and Marcelloni, 2019; Torabi and Taboada, 2019	Society	Fact checking	Fake news articles	English
Ferreira and Vlachos, 2016; Bondielli and Marcelloni, 2019; Torabi and Taboada, 2019	Society, technology	Rumour detection	Rumours	English
Shu et al., 2018; Bondielli and Marcelloni, 2019; Zhang and Ghorbani, 2019	Society, politics	Fake detection	Fake news articles	English
Horne and Adali, 2017; Zhang and Ghorbani, 2019; Ahmed et al., 2018	Politics	Fake detection	Fake news articles	English
Burfoot and Baldwin, 2009; Horne and Adali, 2017; Zhang and Ghorbani, 2019	Politics, economy, technology, society	Fake detection	Satire	English
Horne and Adali, 2017; Zhang and Ghorbani, 2019	Politics	Fake detection	Fake news articles	English
Torabi and Taboada, 2019	Society	Fact checking	Fake news articles	English
Ott et al., 2011; Viviani and Pasi, 2017; Ahmed et al., 2018	Tourism	Fake detection	Fake reviews	English
Riedel et al., 2017; Aldwairi and Alwahedi, 2018; Thota et al., 2018	Politics, society, technology	Fake detection	Fake news articles	English
Posadas-Dur n et al., 2019	Science, Sport, Economy, Education, Entertainment, Politics, Health, Security, Society	Fake detection	Fake news articles	Spanish
Dutta et al., 2019	Politics, society	Fake detection	Fake news articles	English
Rashkin et al., 2017; BarrÃn-Cedeno, 2019	Politics	Fact checking	Fake news articles	English
BarrÃn-Cedeno, 2019	Politics	Fact checking	Fake news articles	English
N-rregaard et al. 2019	Politics	Fake detection	Fake news articles	English
Jang et al., 2019	Politics	Fake detection	Fake news articles	English
Papadopoulou et al., 2019	Society	Fake detection	Fake news content	English, Russian, Spani
Boididou et al., 2018	Society	Veracity classification	Hoaxes	English, Spanish, Dutc
Jwa et al., 2019	Politics, society, crime, sport, economy, technology, health	Fake detection	Fake news articles	English
Zheng et al., 2017	Society	Clickbait detection	Clickbait	Chinese
Tam et al., 2019	Politics, technology, science, crime, fraud and scam, fauxtography	Rumour detection	Rumours	English

1	Language	Size	Physical news content	Rating scal	Media platform	Spontanei	Availabilit	Extraction
2	English	18,912 reviews (9,456 fake reviews and 9,456 trustful reviews)	Text	2 values (f	Mainstream	Yes	Yes	No
3								
4	English and German	330 rumourous conversations (159 are true, 68 are false and 103 remained unverified) and	Text	3 values (t	Social media (twitter)	Yes	Yes	No
5	English	60 million streaming tweets and 1,049 events annotated with credibility scores	Text	5 values (C	Social media (twitter)	Yes	Yes	Yes (Octo
6	English	2,283 Facebook news from 9 facebook news pages (73.18% mostly true)	Text	4 values (	Social media (facebook)	Yes	Yes	Yes (Sept
7	English	15,500 posts from 32 pages (14 conspiracy and 18 scientific) among which 8,923 (57.6%) are hoax	Text	2 values (?	Social media (facebook)	Yes	Yes	Yes (July :
8	English	12,836 human labeled short statements from POLITIFACT.COM?s API (1,050 pants-fire)	Text	6 values (;	Mainstream + social media (facebook, twitter)	Yes	Yes	Yes (2007
9	English	221 statements from two websites (politifact.com and Channel 4)	Text	5 values (t	Mainstream	Yes	Yes	No
10	English	185,445 claims extracted from Wikipedia	Text	3 values (	Mainstream	No	Yes	No
11	English	300 claims, and 2,595 associated article headlines (47.7% true, 15.2% false, 37.1 unverified)	Text	3 values (t	Mainstream + social media (twitter)	Yes	Yes	No
12	English	422 news (211 fake news and 211 real news)	Text, images	2 values (f	Mainstream + social media (twitter)	Yes	Yes	No
13								
14	English	225 stories from political news websites	Text	3 values (r	Mainstream	Yes	Yes	Yes (2014
15	English	4,000 real news	Text	2 values (r	Mainstream	Yes	Yes	No
16		samples and 233 satire news samples						
17	English	2,283 news samples from Facebook	Text	4 values (	Social media (facebook)	Yes	Yes	Yes (2016
18	English	1,692 news article (1,380 from BuzzFeed dataset and 312 from Snopes dataset)	Text	4 values fc	Mainstream	Yes	Yes	No
19				false, and (fully) false)				
20	English	800 reviews (400 truthful and 400 gold-standard deceptive reviews from TripAdvisor)	Text	2 values (t	Social media (TripAdvisor)	No	Yes	No
21	English	49,972 articles (3,678 agree, 840 disagree, 8,909 discuss, and 3,654 unrelated)	Text	4 values (	Mainstream	Yes	Yes	No
22	Spanish	971 news (491 true topics and 480 fake topics)	Text	2 values (t	Mainstream	Yes	Yes	Yes (Janu
23								
24	English	6,337 articles (50% real, 50% fake)	Text	2 values (t	Mainstream	Yes	Yes	No
25								
26	English	33,063 news articles (10,483 from PolitiFact.com and 22,580 from unreliable sources (5,750 trust	Text	6 values fc	Mainstream	Yes	Yes	No
27	English	51,294 articles (5,737	Text	2 values (;	Mainstream	Yes	Yes	No
28		propagandistic and 45,557 trustworthy)						
29	English	713000 articles	Text	2 values (t	Mainstream	Yes	Yes	Yes(Febru
30	English	3472 (1387 fake (16453 tweets) and 2085 real (56651 tweets))	Text	2 values (f	social media (twitter)	Yes	Yes	Yes (Janu
31	English, Russian, Spanish, Arabic, German, Catalan, Japanese, and Portuguese	380 videos and 77258 tweets	Videos, text	2 values	social media (YouTube, Facebook, Twitter)	Yes	Yes	Yes (April
32	English, Spanish, Dutch, French	15629 posts	Text, images, videos	2 values	social media (Twitter)	Yes	Yes	Yes (2012
33	English	287000 articles	Text	4 values	Mainstream	Yes	Yes	Yes (April
34	Chinese	14922 headlines	Text	2 values	Mainstream + social media (Wechat)	Yes	Yes	No
35	English	1022 rumours and 4 million tweets	Text	2 values	social media (Twitter)	Yes	Yes	Yes (May
36								

Data set structure

Data set under construction

→ all instances in data set are **fact checked** by researcher

or **debunked** by fact checking organizations

Data set formation stages:

Identification: 479 fact checked like-farming fake news (2017-2022) from 49 different identified like-farming post resources

Screening: 436 identified emotional like-farming fake news posts in Greek or automatically translated for Greek Facebook users. 43 posts excluded due to fact checking ambiguity

Eligibility: Maximum 5 posts selected for each theme type from every resource (n=153). 3 posts excluded due to narrowing down the study protocol

Included: 150 posts

Data set structure & annotation complexity

Data set structure is not limited in these metadata entries.

-emotional like-farming posts with:

→ stollen, manipulated content or repurposed fake-news content

→ content similarities across former ghost interconnected like-farming pages

→ internet links possibly stripped from content after a while

⇒ complex production and consumption design that multiplies annotation criteria and data set curation standards (post date, like-farming page status, watermarks etc)

Annotation and processing complexity

Like farming understanding

-intrasemiotic & intersemiotic analysis→ annotation indicators based on:

Systemic Functional Grammar

Visual Grammar

Multimodal Critical Discourse Analysis

Computer Mediated Discourse Analysis

-Natural Language Processing→

-current python library/toolkit affordances (e.g. Pandas, NLTK, Textstat)

-previous NLP research on other similar type fake-news, mainly click baits

⇒ transdisciplinary & interdisciplinary approach in data analysis

Χαρακτηριστικά Τίτλων click bait	Chakraborty, A., Paranjape, B., Kakarla, S. & Ganguly, N. (2016)	[illegible] (Biyani, Tsioutsiouliklis & Blackmer, 2016)	
Αριθμός λέξεων	Μεγαλύτερος	[illegible]	Μικρότερη πυκνότητα πληροφορίας από τυπικούς τίτλους (Marquardt, Kanagri, Vardhan, Vivek & Shobha, 2017)
Έκταση λέξεων	Μικρότερη	[illegible]	
Ονόματα	Σπάνια αναφορά	Σπάνια αναφορά	
Πλήθη φωνηέντων	Συχνή [illegible]		
Ύφος, Ποικιλία	Καθημερινός λόγος, λέξεις [illegible], Internet slang (συζ[illegible])	[illegible]	
Συντακτικό (dependencies)	Μεγάλη απόσταση μεταξύ εξαρτημένων όρων. [illegible] (Watts, 1996, Wolff, 1996)		
Stop Words	Συχνή χρήση [illegible] στα n-gram [illegible]		
Ανάλυση μορφολογική	Σύνθετες λέξεις [illegible]	[illegible] (Biyani, Tsioutsiouliklis & Blackmer, 2016)	
Ανάλυση συναισθήματος	"Υπερβολικές λέξεις" με "πολύ-θετικό συναίσθημα"	[illegible]	Συναίσθημα θετικό, [illegible]
Στίξη	Άσκοπα μοτίβα π.χ. "!!!,?"	[illegible] (Biyani, Tsioutsiouliklis & Blackmer, 2016)	[illegible] (Marquardt, Kanagri, Vardhan, Vivek & Shobha, 2017)
Τυπικές εκφράσεις (n-grams)	[illegible]	[illegible]	
Συγκέντρωση [illegible] (pos-dep)	[illegible]	[illegible]	
Αναφορά στον [illegible]	[illegible] Possessive case	[illegible]	
3N-grams	[illegible]	[illegible]	[illegible]
Αντιστοίχιση POS	Tags [illegible]	[illegible] POS [illegible]	
NER Ονόματα	[illegible] lower case [illegible]		
URL		[illegible]	
[illegible] Πληροφοριακή [illegible]		[illegible] (Chua, Pal & Banerjee, 2021) Τίτλος	
Τοποθέτηση [illegible]		[illegible] (Chua, Pal & Banerjee, 2021)	
[illegible] (gratification)		Προσωπική ανάγκη: [illegible] (Chua, Pal & Banerjee, 2021)	
		[illegible]	
		[illegible]	
Error analysis			
		[illegible]	

Μεταβλητές παρουσίασης -->	6 μεταβλητές click bait (τίτλος και εικόνα)	[illegible]	Εξαγωγή από βιβλιογραφία για τα χαρακτηριστικά σε τίτλους
M	Μικρότερη πυκνότητα πληροφορίας από τυπικούς τίτλ[illegible]	Απουσία βασικής πληροφορίας	πληροφοριακό κενό Loewenstein (1994), αόριστες αντωνυμίες (Chen, Conroy, and Rubin, 2015
		Αναπάντητες ερωτήσεις	καταστροφή της αφηγηματικής δομής της ανεστραμμένης πυραμίδας
		[illegible]	μυστήριο και αποκάλυψη ενδιαφέροντος (Molek-Kozakowska, 2013: 183), [illegible]
		Αριθμοί και λίστες	
	2. Εντυπωσιακή έκφραση	Προστακτική	
		Κλητική	
		[illegible]	
	3. Επανάληψη και [illegible]	Φωνητική επανάληψη	στοιχεία [illegible] Noriega (1997: 68)
		Επανάληψη του [illegible]	
		[illegible]	
	4. Υπερβολική έκφραση/έμφαση	Σχήμα υπερβολής	
		Συγκρίσεις [illegible] και υπερθετικός βαθμός	ένταση, έμφαση ([illegible], 2001, Molek-Kozakowska, 2013)
		[illegible]	
		Νεολογισμοί με το "υπέρ"	υπέρ, [illegible] + προσδιορισμοί που αυξάνουν την ένταση [illegible], 2016:74
Μεταβλητές περιεχομένου-->	5. Ελαφριά νέα	Ελαφριά ή [illegible] περιεχόμενα	(Reinemann et al., 2012)
		[illegible]	
	6. Εντυπωσιακά οπτικοακουστικά στοιχεία	[illegible]	
		[illegible]	
		[illegible]	
	8 τύποι (τίτλος και εικόνα)	(Biyani, Tsioutsiouliklis & Blackmer, 2016)	
	[illegible]	[illegible]	
	[illegible]	[illegible]	
	[illegible]	[illegible]	
	[illegible]	[illegible]	
	[illegible]	[illegible]	
	[illegible]	[illegible]	
	[illegible]	[illegible]	
	[illegible]	[illegible]	

Data frame analysis

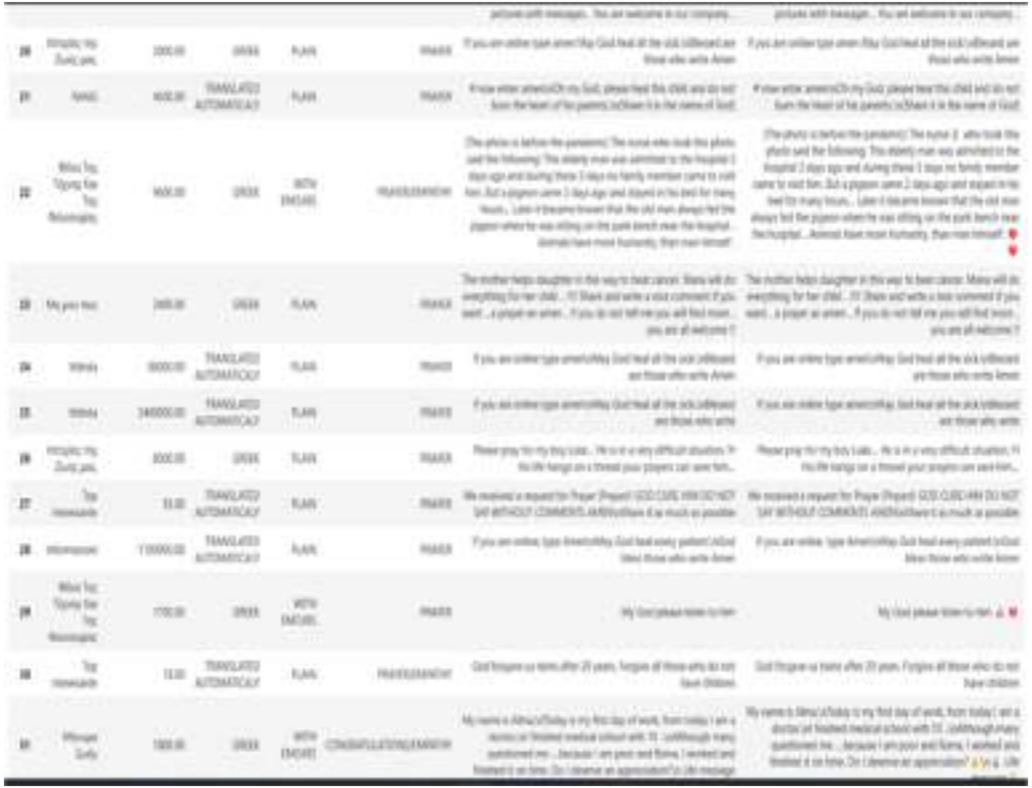
Using Pandas methods to:

-display data frame columns,

types, shape,

format,

length and unique column name

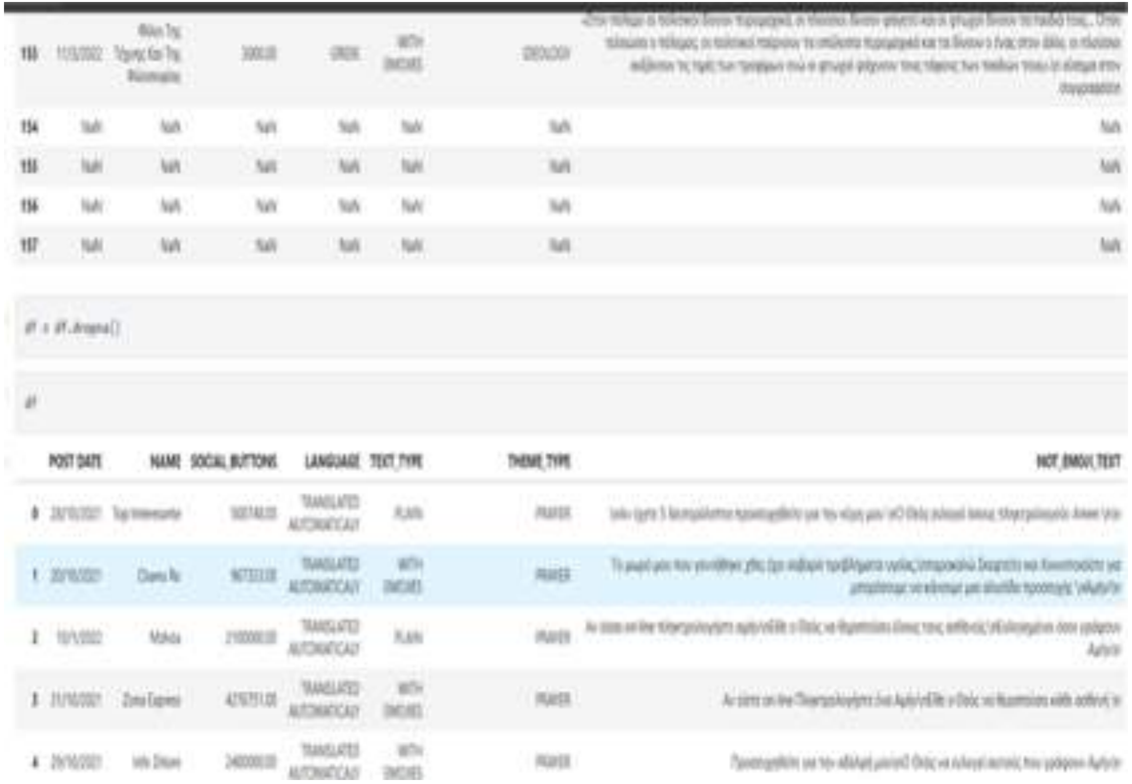


Data frame analysis

-change index,

drop columns,

delete NaN values



	POST DATE	NAME	SOCIAL_BUTTONS	LANGUAGE	TEXT_TYPE	THEME_TYPE	NOT_EMOJI_TEXT
0	[illegible]	[illegible]	[illegible]	TRANSLATED AUTOMATICALLY	PLAIN	PRAYER	[illegible]
1	[illegible]	[illegible]	[illegible]	TRANSLATED AUTOMATICALLY	WITH EMOJIES	PRAYER	[illegible]
2	[illegible]	[illegible]	[illegible]	TRANSLATED AUTOMATICALLY	PLAIN	PRAYER	[illegible]
3	[illegible]	[illegible]	[illegible]	TRANSLATED AUTOMATICALLY	WITH EMOJIES	PRAYER	[illegible]
4	[illegible]	[illegible]	[illegible]	TRANSLATED AUTOMATICALLY	WITH EMOJIES	PRAYER	[illegible]

Data frame analysis

-apply a groupby function

and perform a descriptive statistic on axis

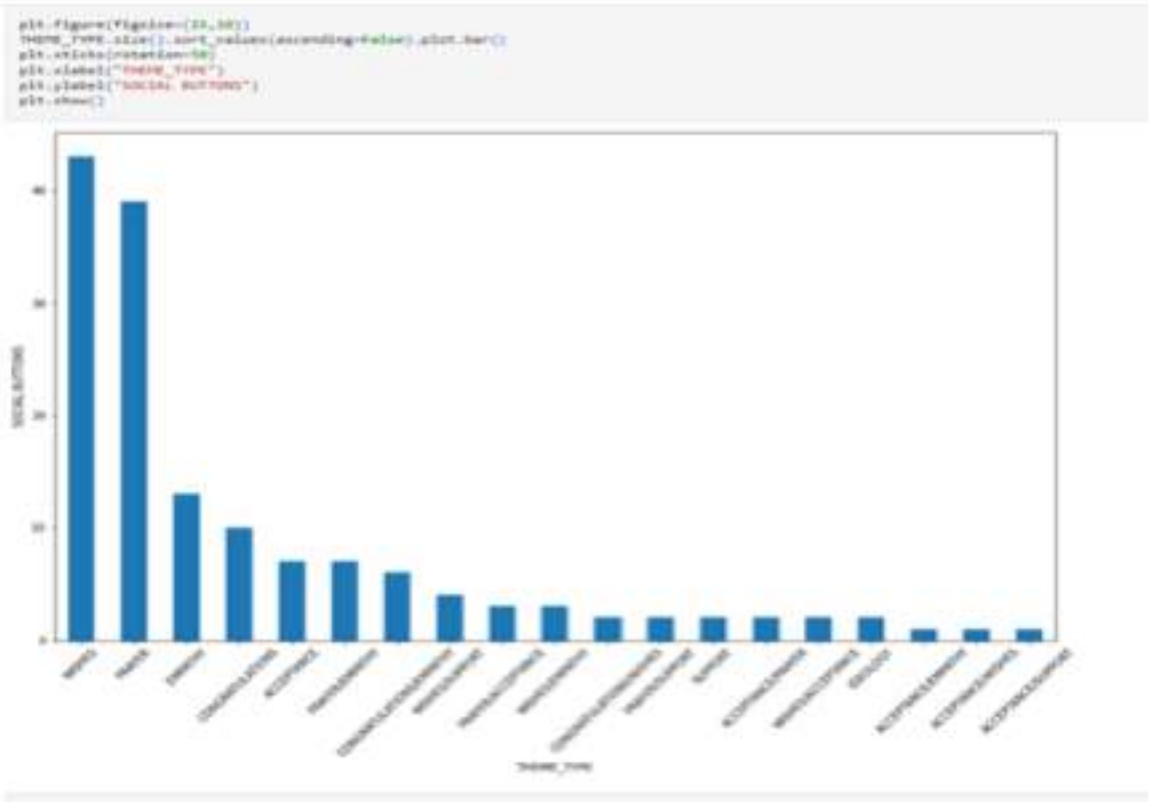
```
# Groupby
TEXT_TYPE = df.groupby("TEXT_TYPE")

# Summary statistic of all
TEXT_TYPE.describe().head()
```

	SOCIAL_BUTTONS							
	count	mean	std	min	25%	50%	75%	max
TEXT_TYPE								
PLAIN	69.0	106658.446232	494895.676573	1.0	437.0	1300.0	4075.0	3400000.0
WITH EMOJIES	81.0	159541.098765	602355.648109	15.0	346.0	1300.0	3700.0	4276751.0

Data frame analysis

-print indexed column text and concatenate

-visualise sorted values using matplotlib.pyplot



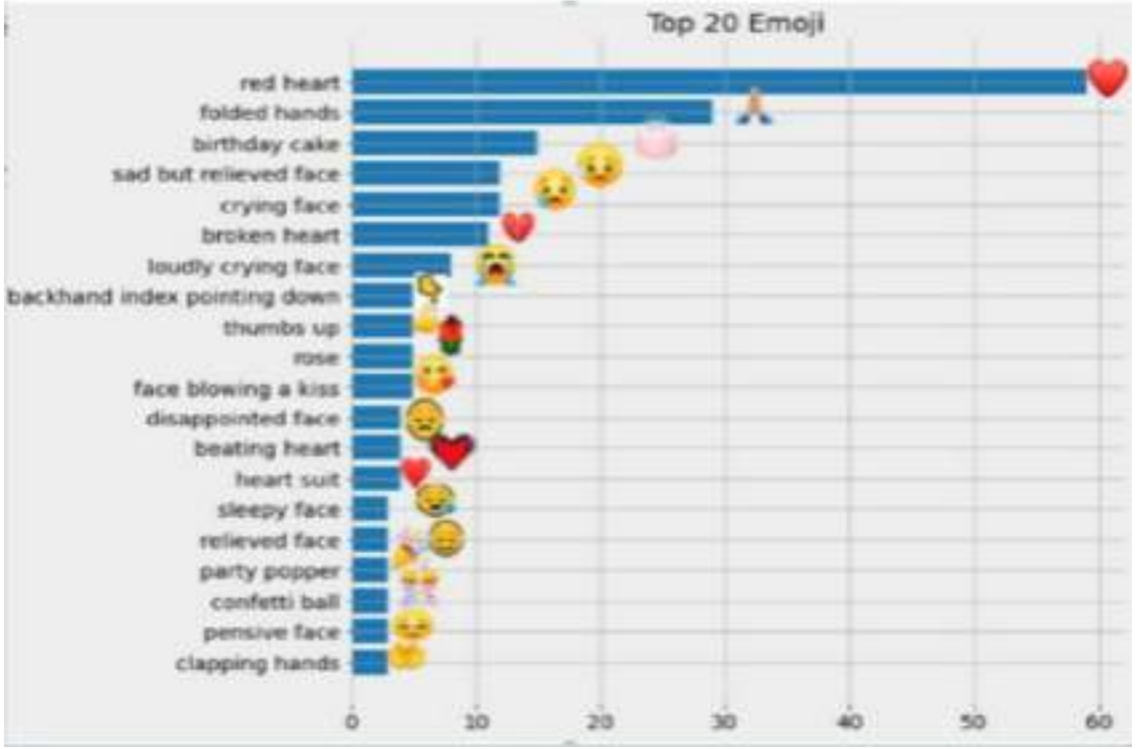
Data frame analysis

-decode,

-count unique,

–total count,

plot statistics of emojis/emoticons



Data frame analysis

-join
-split
-print text
length

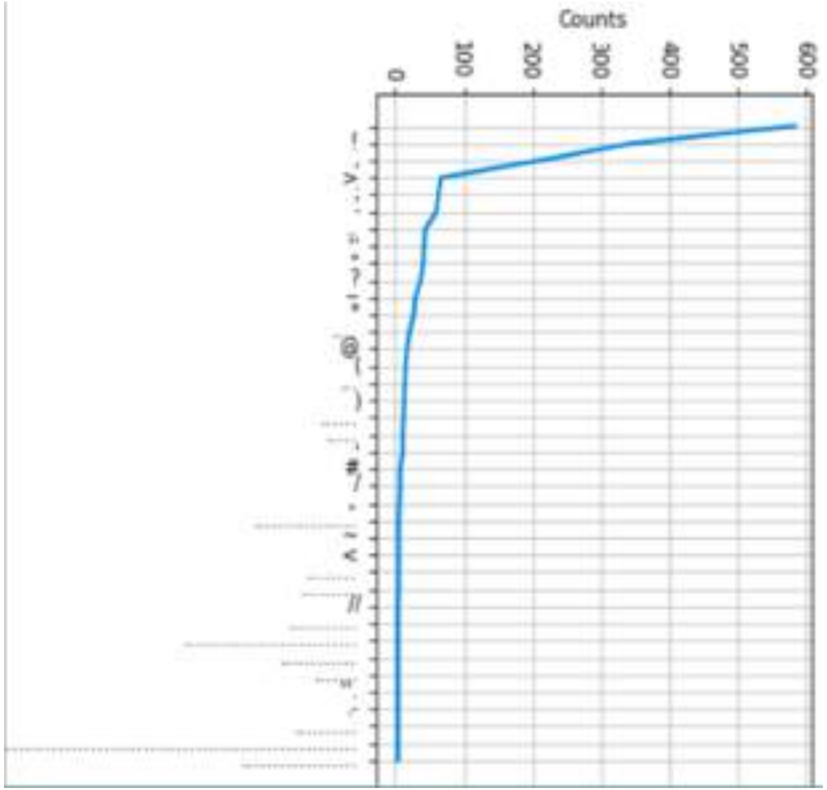
NLP using NLTK

Cleaning text

-inspect nltk stopword list -insert new list & set final stopword list

-lowercase when needed

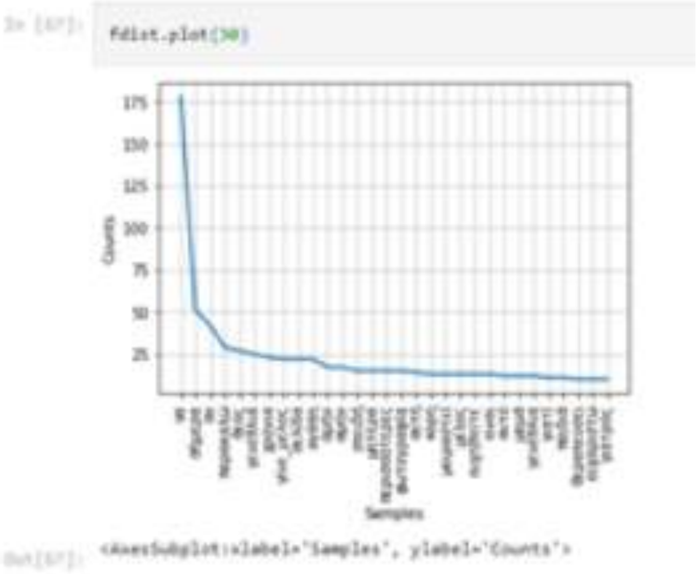
-extract http & punctuation using RegEx, filter text using for loops +plot



NLP using NLTK

-get frequency distribution of words or emojis/emoticons in cleaned text

-plot & interpret



- **Passive representations of vulnerable social groups**
- **Constructions of otherness and group identity**

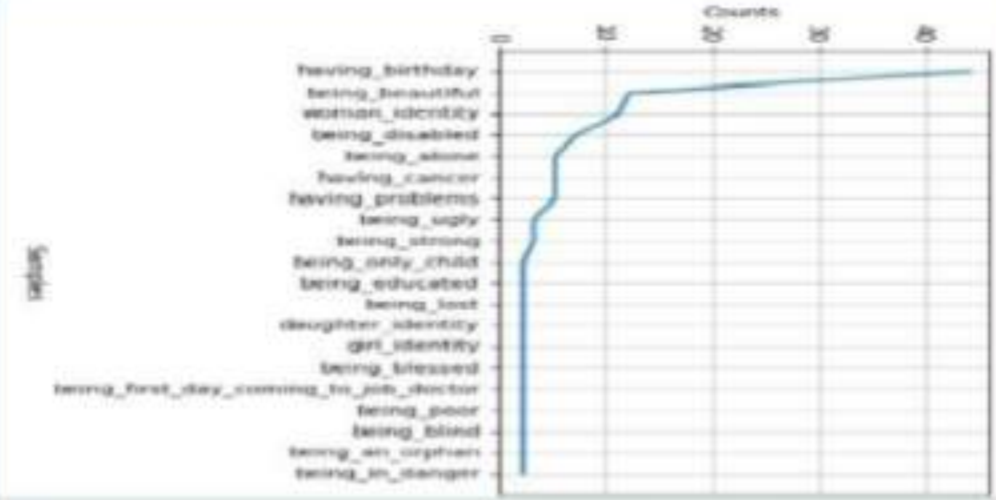
-Relational processes: narrow identity representations

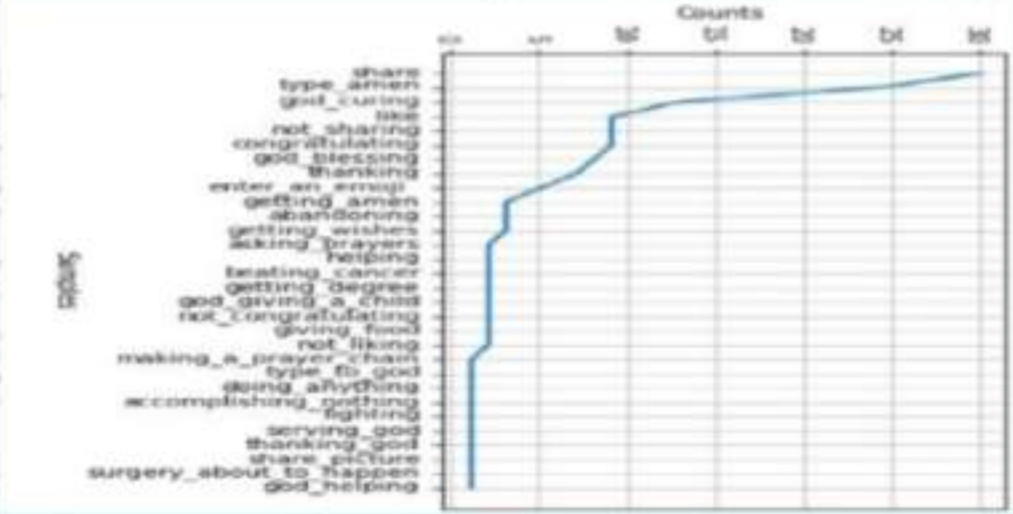
▬ The confined in body

-Material processes:

▬ Mediating for the vulnerable with Facebook tokens

▬ The non responding Others



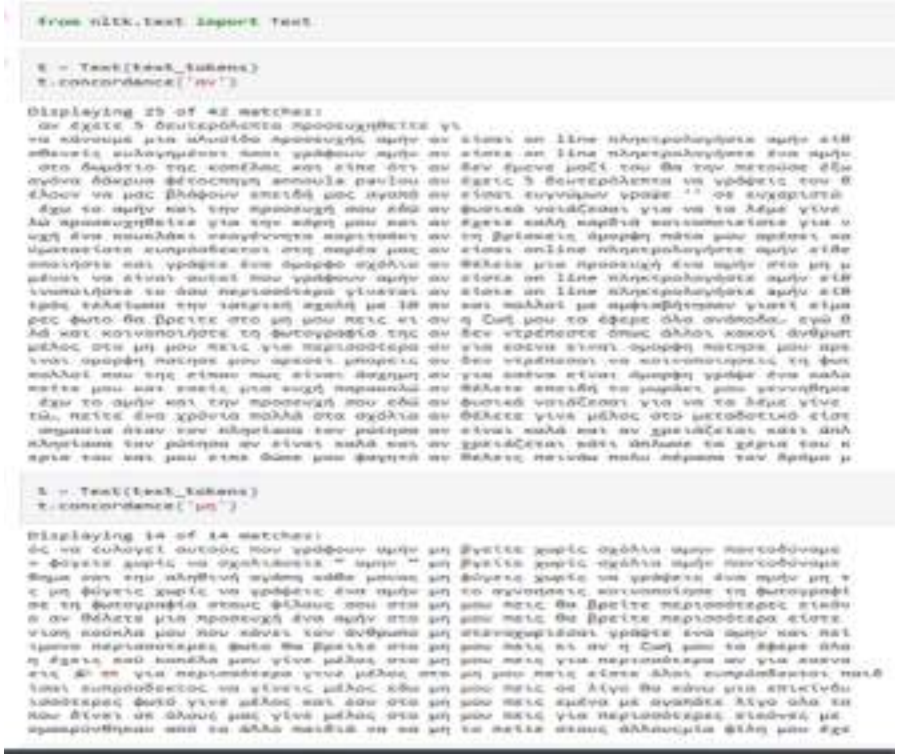


NLP using NLTK

-use Bigram Collocation Finder to get bigram association measurements + frequency distribution+ dispersion plots

-use n-grams to inspect text +focus on certain features

-use concordances for SFL+ CDA on targeted features

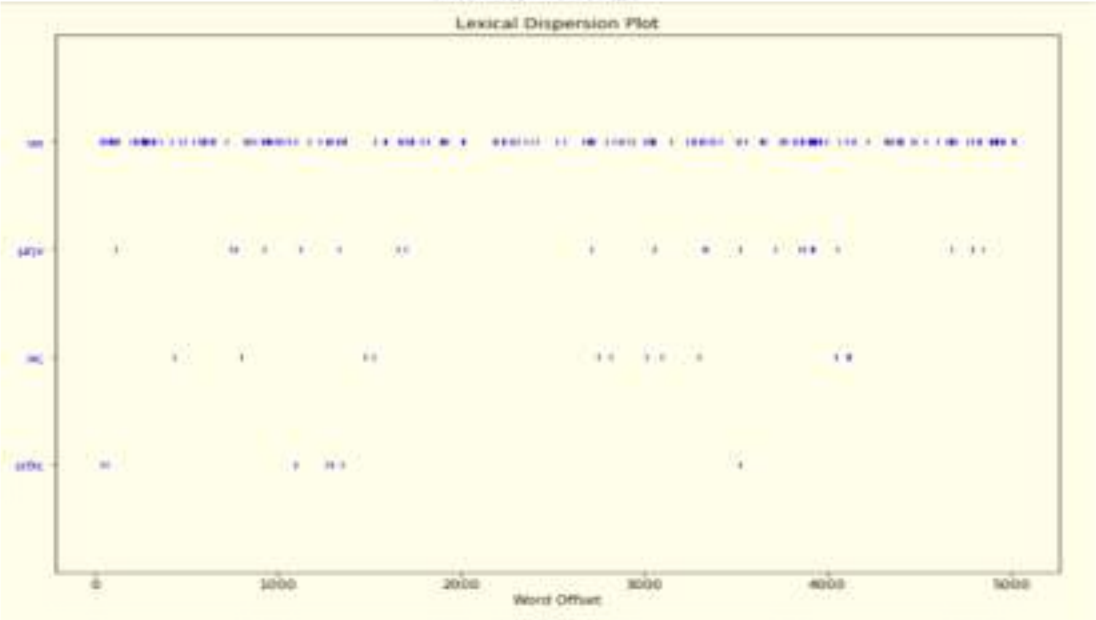

```
from nltk.text import Text

t = Text(text_tokens)
t.concordance('αν')

Displaying 25 of 42 matches:

t = Text(text_tokens)
t.concordance('μη')

Displaying 14 of 14 matches:
```

NLP using NLTK

-use dispersion plots for getting a group understanding of targeted

features

```
# the following command can be used to increase the size of the plot using width and hight specifications
plt.figure(figsize=(12, 9))
targets=['να','μην','ας','είθε']
dispersion_plot(text_tokens, targets, ignore_case=True, title='Lexical Dispersion Plot')
```



NLP using Textstat

-sentence count

-readability scores

→ even wrong outcomes

give an understanding about

like-farming production design

& Facebook algorithm circumventing practices

NLU using Vader & TextBlob

→ text cleaning for TextBlob, Vader sentiment analysis (NLU) → interpreting data from libraries

* different training process

```
print(df["textblob_polarity_bayes"].value_counts())
```

```
pos          103
neutral       34
neg           14
Name: textblob_polarity_bayes, dtype: int64
```

```
score = df["compound_vader"].values
sentiment = []
for i in score:
    if i >= 0.05 :
        sentiment.append('pos')
    elif i <= -0.05 :
        sentiment.append('neg')
    else:
        sentiment.append('neutral')
df["Plain_text_VaderSentiment_LABEL"] = sentiment
df.head()
```

```
print(df["Emoji_text_VaderSentiment_LABEL"].value_counts())


#pos          127
#neg           22
#neutral        2
#Name: Plain_text_VaderSentiment_LABEL, dtype: int64
-->άρα εδώ τα emojis αλλάζουν προς το θετικότερο ένα αρνητικό μήνυμα
```

```
pos          134
neg           15
neutral        2
Name: Emoji_text_VaderSentiment_LABEL, dtype: int64
```

```
print(df["emoji_textblob_bayes_sentimentlabel"].value_counts())

#pos          103
#neutral       34
#neg           14
#Name: textblob_polarity_bayes, dtype: int64-->ΧΩΡΙΣ EMOJI ΚΕΙΜΕΝΟ
-->άρα τα emojis αλλάζουν ΕΔΩ τον τόνο ,μειώνοντας την ουδετερότητα..
```

```
pos          97
neg          30
neutral      24
Name: emoji_textblob_bayes_sentimentlabel, dtype: int64
```

Data appropriation

Visualisations:

matplot.lib, py.plot + softcode libraries

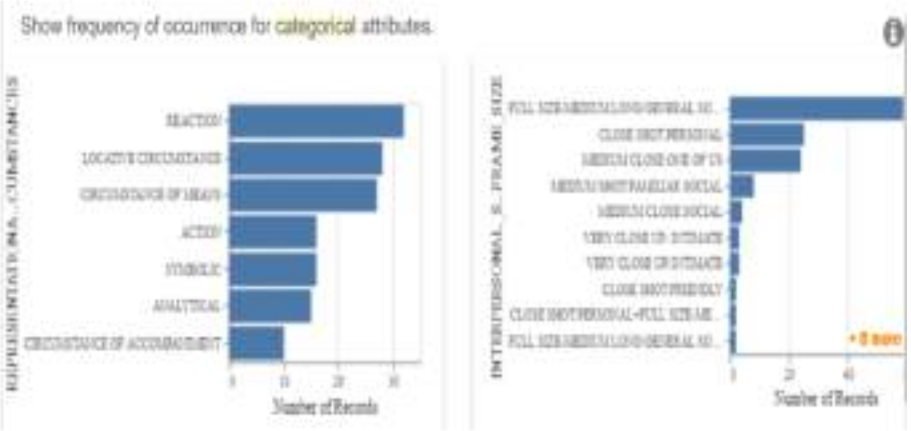
- quick inspection of data patterns

-grouped data columns statistics

⇒ comparing and focusing analysis

⇒ spotting mistakes

⇒ using basic pandas methods for cleaning annotation noise



Data appropriation

→emoji/emoticon translation (EMOJI & DEMOJI libraries)

→in context emoji//emoticon

translation

```
import emoji
```

```
text5=text4.str.replace("_", " ")
text6=text5.str.replace(":", " ")
text7=text6.str.replace("face", "")
text8=text7.str.lower().str.replace('\n',' ')
text9=text8.str.lower().str.replace('backhand index pointing down','like there')
text10=text9.str.lower().str.replace('face with open mouth','astonished')
text11=text10.str.lower().str.replace('woman health worker','nurse')
text11=text10.str.lower().str.replace('four leaf clover','good luck')
text12=text11.str.lower().str.replace('four leaf clover','good luck')
text13=text12.str.lower().str.replace('double exclamation mark','!!')
text14=text13.str.lower().str.replace('open hands','supplication')
text15=text14.str.lower().str.replace('folded hands','praying')
text16=text15.str.lower().str.replace('thumbs up','like')
```

Tensions between real +perceived representation affordances

→ decorative > clarifying word clouds

→ no adequate emoji representation in plots

→ BERTopic

modeling technique > n-grams

	Topic # 01	Topic # 02	Topic # 03
0	amen	birthday	years
1	god	today	twins
2	write	wish	20
3	love	happy	good
4	page	wished	pregnancy
5	share	wishes	children
6	like	old	man
7	please	make	single
8	girl	please	days
9	say	years	congratulate

```
topic_model.get_topic(-1)
```

```
[('photo', 0.22849291214251222),
 ('share', 0.16967127849622485),
 ('hi', 0.14398329740979046),
 ('wish', 0.14139273208018738),
 ('birthday', 0.13754442275301546),
 ('friends', 0.1322772861818923),
 ('disabled', 0.1322772861818923),
 ('think', 0.12400148124660015),
 ('problem', 0.10937868529310978),
 ('christmas', 0.10937868529310978)]
```

Discussion

NLP is a professional digital competence that should be more advanced in Higher Education

Challenges to be addressed:

- error analysis practices→ reflect on non English NLP restrictions + linguistic contribution in digital humanities
- research priorities +NLP goals: corpus criteria, data set formation practices
- demand for scaffolded NLP +NLU didactic strategies

different data mining approaches, cleaning text methods

different python libraries use: informal, formal speech analysis

Discussion

Tensions to overcome:

- instrumental approach of NLP (a tool that can be handled with elementary skills)
- over relying on emerging digital literacy skills or in other coding languages experience
- strong classification boundaries + context frame (Bernstein, 1975: 88-89) impede interdisciplinary pedagogy and didactics

Tensions to to be anticipated for scaffolding practices:

- different understandings on situated awareness may harm task performance and deprive learner agency
- perceived and real NLP affordances (positive or negative) can be either way productive

Discussion

Needs to attend

- **danger of imposing a computational/technocratic point of view on digital humanities studies and a tool didactic approach on AI**

→ need for bridging the divide: different communication approach +educational initiative in digital humanities

- **digital humanities curriculum should be based on digital humanities needs analysis in research and teaching**

→ need to form a digital humanities Grammar: coding, syntax, pragmatics (ontologies, networks and mixed approaches)

→ need for an informed educational approach to connectivism and its relation to knowledge, learning and truth

→ need for curriculum alignment and professional development strategies that are research domain specific

THANK YOU!