Healthcare Applications with Natural Language Processing (NLP)

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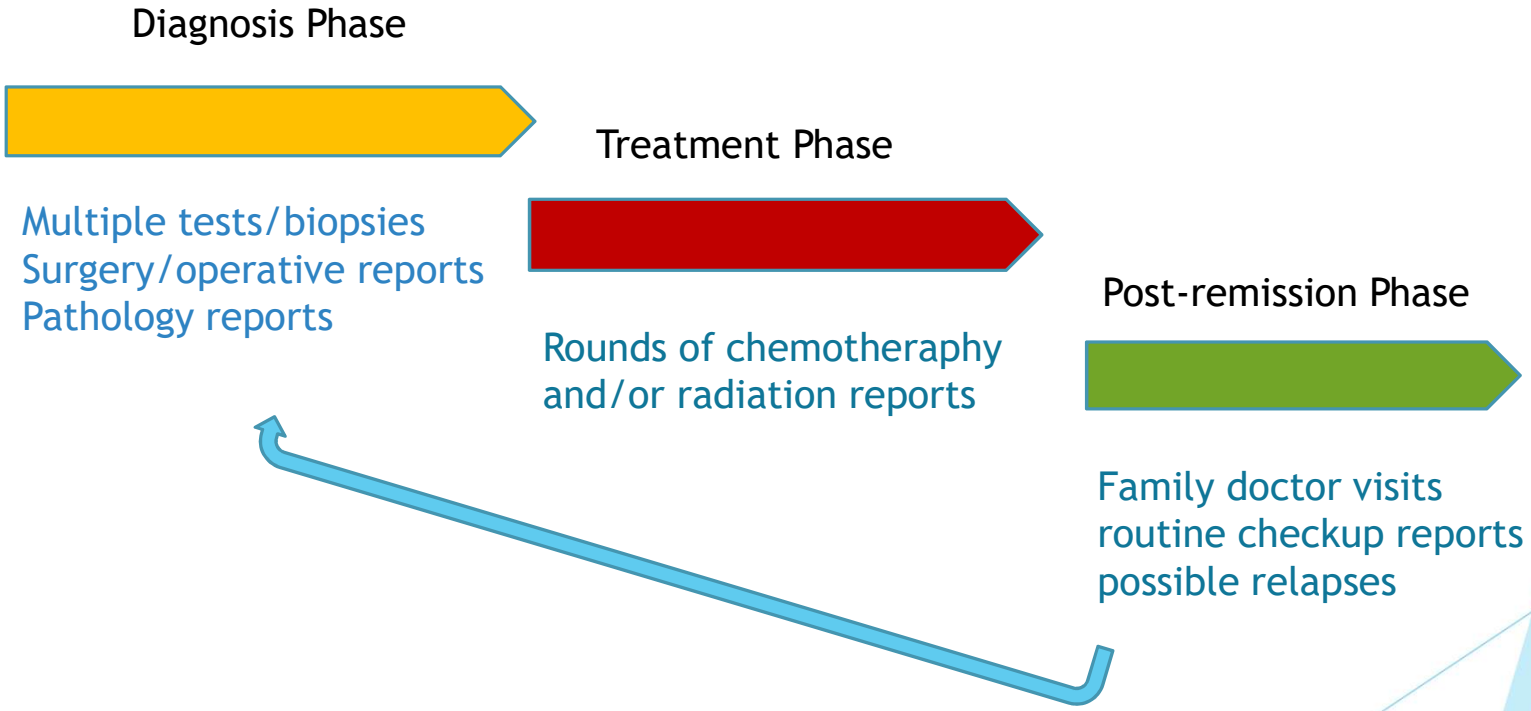
Why NLP? First Answer: Gold mines

- Huge amounts of unstructured data
  1. “Official” documents, e.g., medical reports, clinical documents
  2. User generated content, e.g., blogs, text messages
- Machine Learning in health care still predominantly based on structured data, e.g. Electronic Health Records (EHR), insurance data
- Take home message: ***huge opportunities to use such unstructured data for better patient care***

Use Case for Clinical Documents: Cancer Care



Use Case for Official Documents: Cancer Care

- Current practice:
  - very siloed, different types of documents rarely linked together
    - Used mainly to make the next "local" decisions
    - Key findings over the whole journey not consolidated "holistically"
  - Documents read/interpreted only by humans
    - Lack of health care resources means significant time delay, e.g., many months
- Our ongoing work is to use NLP and machine learning to automatically extract "*fields of interest*" from clinical documents
  - Improving detection of reportable cancer
  - Identifying diagnostic groups
  - Predicting treatment response
  - Stratifying risks for relapses

E.g., A Breast Cancer Surgical Report:

staging, location, size, negation, etc.

Final Diagnosis ::
A. Right mastectomy including nipple and skin showing:
1. Two loci of recurrent invasive ductal carcinoma of primary breast derivation.
2. Both are located in the upper one-half of the specimen in the vicinity of prior surgery with one deposit designated at the 11:30 o'clock position

measuring 1.5 x 1.2 cm with the other at roughly the 10 o'clock position measuring 1.2 x 1 cm.
3. These deposits are separate from one another by 3 cm.
4. Both are very similar histologically and each have pleomorphic somewhat apocrine nuclei (score 3); are 50% gland forming (score 2) and show a variable mitotic rate focally above 7/mm2 (score 3) and thus overall Nottingham score is 8/9, grade 3.
5. Prognostic marker status: previously performed on both nodules through Lion's Gate Hospital on prior needle core biopsies (LS19-1426) showing:
   a. Estrogen receptor status positive, Allred score 8/8.
   b. Progesterone receptor negative, Allred score 0/8.
   c. HER2neu by immunohistochemistry negative.
   d. These results are not similar to the original tumor of 2016 (LS16-13442).
   -No lymphovascular invasion identified (extensive retraction artefact around tumoral nests makes assessment difficult)
6. Both deposits of invasive carcinoma harbor a small amount of intratumoral intraductal carcinoma with high-grade apocrine nuclei with no comedo necrosis.

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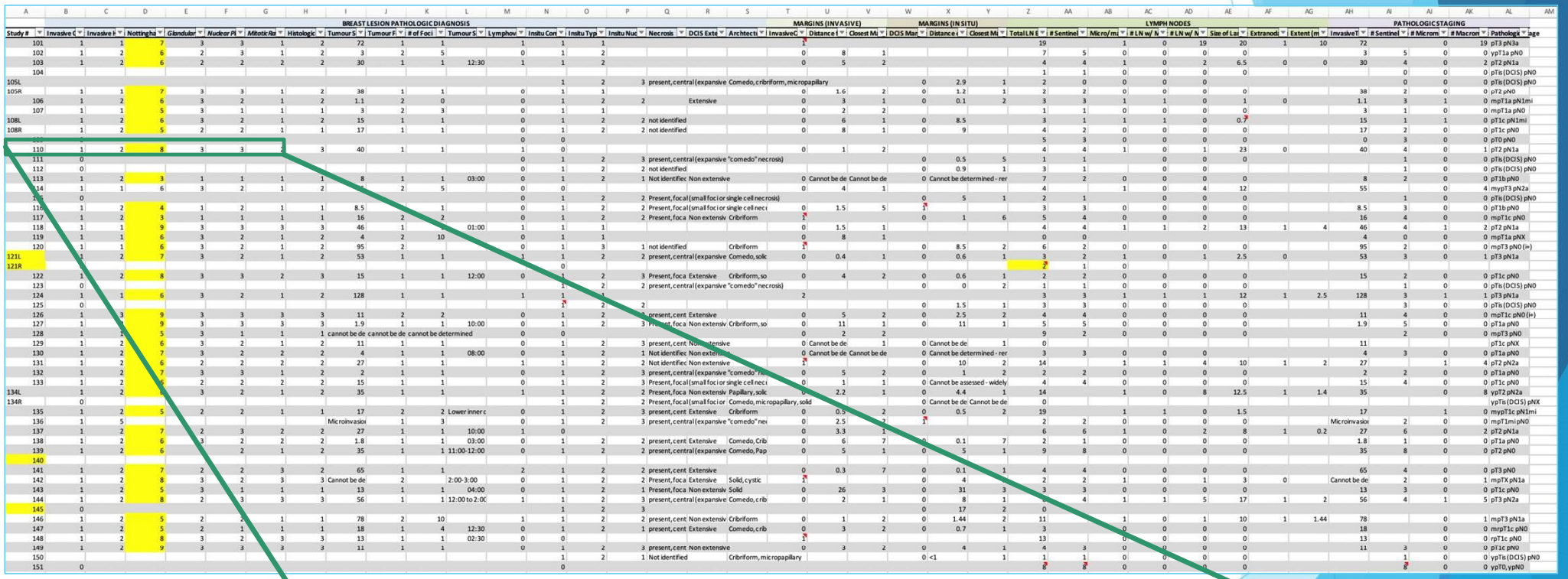
7. Margins:
   a. 11:30 tumor lies at closest approach 2 mm from the blue anterior margin (block A3) - other margins widely negative.
   b. Separate deposit at roughly 10 o'clock involves the anterior margin via a 'tongue' 2 mm in cross dimension (tumour found within cautery at blue anterior ink) and at closest approach is 2 mm from the deep margin (block A7/A8) with other margins widely negative
8. No nipple involvement and all other four quadrants extensively sectioned show no in-situ carcinoma or infiltrating carcinoma.

Output: an Extracted Table of Fol's



Study #	Invasive Carcinoma	Invasive Histologic Type	Nottingham Score	*Glandular Differentiation*	*Nuclear Pleomorphism*	*Mitotic Rate*
110	1	2	8	3	3	2

An Incomplete List of Fields of Interest

Mastectomy

- Study #
- Invasive Carcinoma
- Invasive Histologic Type
- Nottingham Score
- Glandular Differentiation
- Nuclear Pleomorphism
- Mitotic Rate
- Histologic Grade
- Tumour Size (mm)
- Tumour Focality
- # of Foci
- Lymphovascular Invasion
- Tumour Site
- Insitu Component
- Insitu Type
- Insitu Nuclear Grade
- Necrosis
- DCIS Extent
- Archtectural Patterns

Margins

- Invasive Carcinoma Margins
- Distance from Closest Margin
- Closest Margin

- DCIS Margins
- Distance of DCIS from
- Closest Margin (mm)
- Closest Margin DCIS

Lymph Nodes

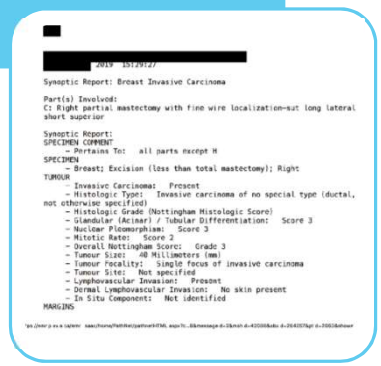
- Total LN Examined
- # Sentinel LN Examined
- Micro/macro metastasis
- # LN w/ Micrometastasis
- # LN w/ Macrometastasis
- Size of Largest Macrometastasis Deposit
- Extranodal Extension
- Extent (mm)

Pathologic Staging

- Invasive Tumour Size (mm)
- # Sentinel Nodes Examined
- # Micrometastatic Nodes
- # Macrometastatic Nodes
- Pathologic Stage

"Automated medical chart review for breast cancer outcomes research: a novel natural language processing extraction system" (BMC May 2022)

Input PDF

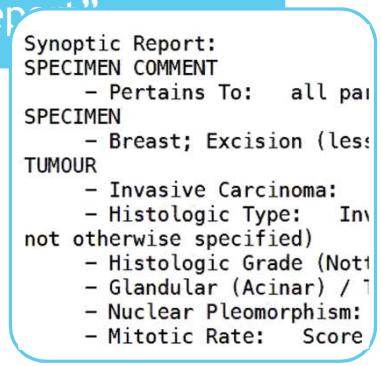


Synoptic Report: Breast Invasive Carcinoma

Part(s) Involved:
C: Right partial mastectomy with fine wire localization-sut long lateral short superior

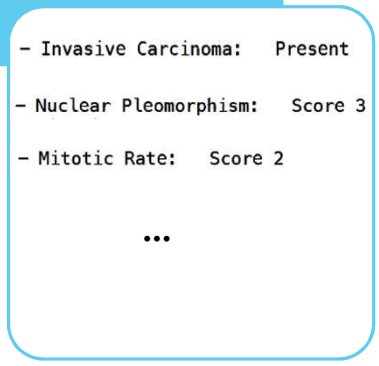
Synoptic Report:
SPECIMEN COMMENT
- Pertains To: all parts except H
SPECIMEN
- Breast; Excision (less than total mastectomy); Right
TUMOUR
- Invasive Carcinoma: Present
- Histologic Type: Invasive carcinoma of no special type (ductal, not otherwise specified)
- Histologic Grade (Nottingham Histologic Score)
- Glandular (Acinar) / Tubular Differentiation: Score 3
- Nuclear Pleomorphism: Score 3
- Mitotic Rate: Score 2
- Overall Nottingham Score: Grade 3
- Tumour Size: 40 Millimeters (mm)
- Tumour Focality: Single focus of invasive carcinoma
- Tumour Site: Not specified
- Lymphovascular Invasion: Present
- Dermal Lymphovascular Invasion: No skin present
- In Situ Component: Not identified
MARGINS

Search for "Synoptic Report"



Synoptic Report:
SPECIMEN COMMENT
- Pertains To: all pa
SPECIMEN
- Breast; Excision (les
TUMOUR
- Invasive Carcinoma:
- Histologic Type: In
not otherwise specified)
- Histologic Grade (Not
- Glandular (Acinar) /
- Nuclear Pleomorphism:
- Mitotic Rate: Score

Isolate each bullet-point



- Invasive Carcinoma: Present
- Nuclear Pleomorphism: Score 3
- Mitotic Rate: Score 2
...

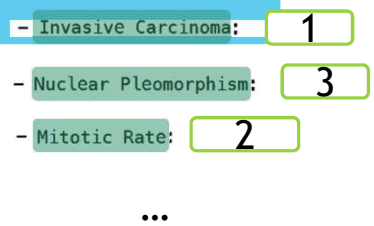
Extract data

- Nuclear Pleomorphism: Score 3
- Invasive Carcinoma: Present
- Mitotic Rate: Score 2
...

Save raw text to Excel

	A	B	C	D
	Study #	Invasive Carcinoma	Nuclear Pleo-morphism	Mitotic Rate
	110	Present	Score 3	Score 2

Encode data



- Invasive Carcinoma: 1
- Nuclear Pleomorphism: 3
- Mitotic Rate: 2
...

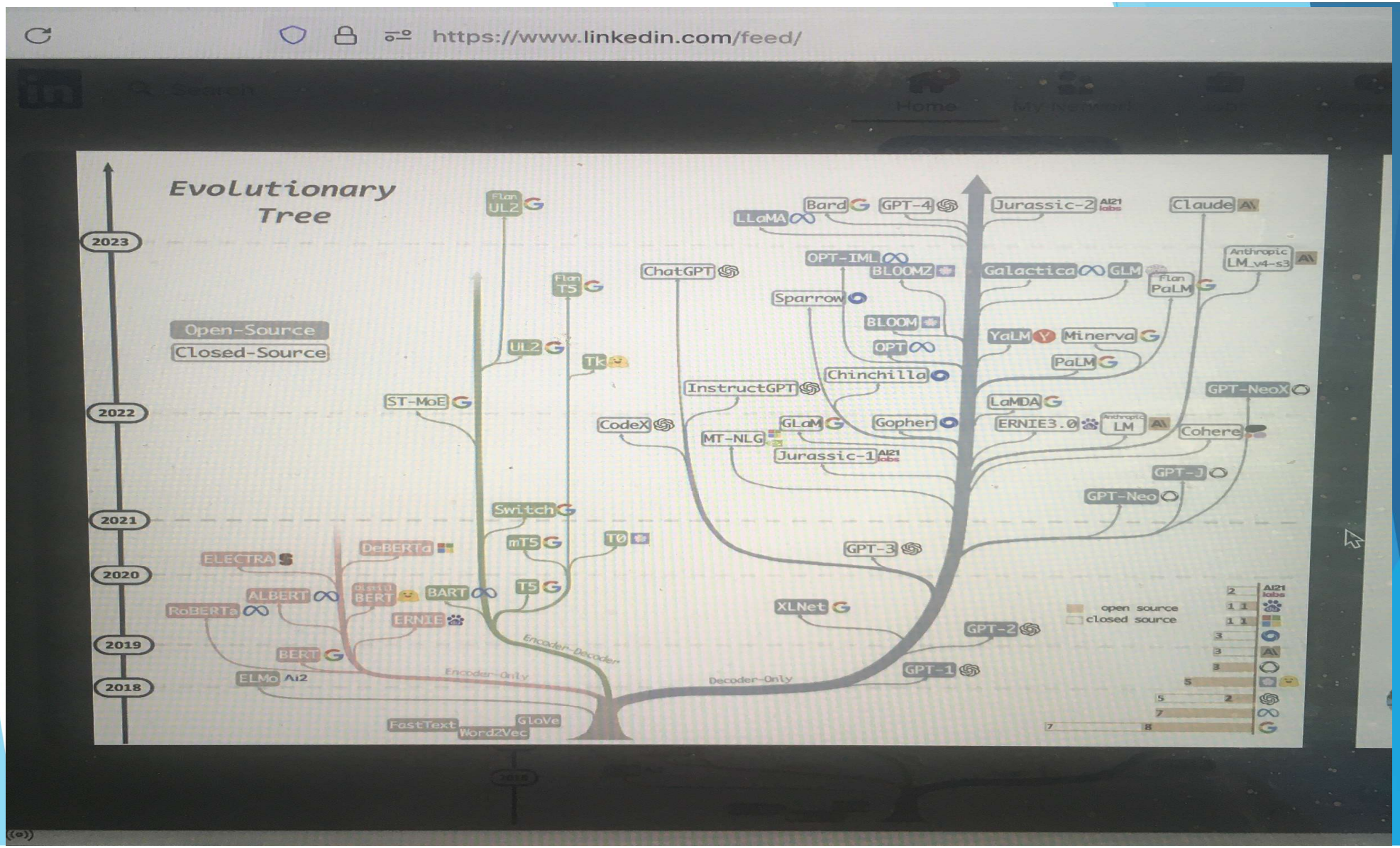
Save encodings to Excel

	A	B	C	D
	Study #	Invasive Carcinoma	Nuclear Pleo-morphism	Mitotic Rate
	110	1	3	2

...

Why NLP? Second Answer: Great Advances

- Pre-trained language models - biggest advances in NLP this decade
  - Trained with a large dataset while remaining agnostic to the specific tasks they will be employed on
  - E.g., BERT: created by Google with from English Wikipedia with 2,500M words
    - NLP -> **Natural Language Understanding**
  - Many variants, e.g., BioBERT, PubMed BERT, RoBERTa
  - Later models, e.g., T5, GPT2, GPT3, and ChatGPT
- Designed to be “fine-tunable” with specific tasks and domains, e.g., questions and answers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Evolutionary Tree
2023
2022
2021
2020
2019
2018
Open-Source
Closed-Source
Flan UL2
Bard
GPT-4
Jurassic-2
Claude
LLaMA
OPT-IML
BLOOMZ
ChatGPT
Galactica
GLM
Anthropic LM_v4-s3
Flan T5
Sparrow
Flan PaLM
BLOOM
YaLM
Minerva
UL2
OPT
Tk
PaLM
Chinchilla
InstructGPT
GPT-NeoX
ST-MoE
LaMDA
CodeX
GLaM
Gopher
ERNIE3.0
Anthropic LM
Cohere
MT-NLG
Jurassic-1
GPT-J
GPT-Neo
Switch
mT5
T0
GPT-3
ELECTRA
DeBERTa
ALBERT
distil BERT
BART
T5
RoBERTa
ERNIE
XLNet
GPT-2
BERT
Encoder-Decoder
Encoder-Only
Decoder-Only
GPT-1
ELMo
AI2
FastText
GloVe
Word2Vec
open source
closed source

Why NLP? BERT Q/A examples

- From: //huggingface.co/tasks/question-answering
- E.g., text: "*I am Sarah and Vancouver is my home*"
  - Q1: "*what is my name*"
  - Ans1: "Sarah"
  - Q2: "*where do I live*"
  - Ans2: "Vancouver"
- E.g., text: "*The Amazon rainforest, also known in English as Amazonia or the Amazon Jungle*"
  - Q1: "*Which name is also used to describe the Amazon rainforest*"
  - Ans: "Amazonia"
- We use it for healthcare applications and mineral mining governance (environmental waste management)

What about User Generated Content (UGC)?

- Clinical documents written by clinicians and healthcare professionals
- What about listening to the patients, their families and care-givers?
  - Their opinions, experiences, needs, feelings, mood, etc.
- How is UGC different from formal documents?
  - Diverse backgrounds
  - Diverse writing styles: use of words, length, may not even be grammatically correct
  - More subjective
  - Different genre: forums, chats, conversations, blogs

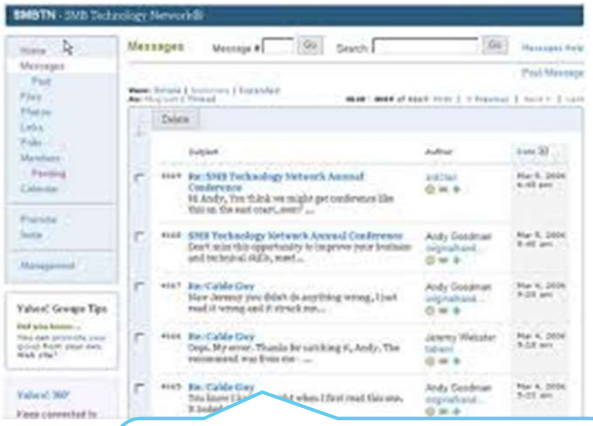
Listening to the Patients

Topic modeling
What are patients talking about? E.g., diet, treatment, doctors, …

Needs detection
What needs are patients seeking?
e.g., health information, social support, …

Dialog acts
Why are patients talking about certain topics?
e.g., explain information on a diet, ask questions on skin rash, sharing emotions on a treatment

Patients' conversations



Discourse coherence
Is what the patient says coherent?

Text Analysis for Chronic Disease Management

- Topic modeling
  - Research task: topic modeling with an ontology
  - Data: mDAWN social media discussions
- Needs detection
  - Research task: needs prediction
  - Data: American Cancer Society online discussion forum data
- Dialog acts
  - Research task: dialog act prediction
  - Data: American Cancer Society online forum data
- Discourse coherence
  - Research task: dementia detection
  - Dementia datasets (speech and text)

Online Discussion Forums, e.g., American Cancer Society

- Understand their needs as a first step to recommending interventions
- But Manual identification of needs too labor intensive and time consuming
- Develop automated algorithms to classify types of needs
  - Data consists of: 52,000+ posts (2006-2016)
  - Collected from the Cancer Survivors Network online peer-support forum (http://csn.cancer.org)

"Neural Prediction of Patient Needs in an Ovarian Cancer Online Discussion Forum" (Canadian AI, 2019)

- **Physical needs:** *"I have finished the 6 rounds of carbo/taxol and am slowly recovering from the assault of the treatment. Has anyone experienced joint pain after tx? I've noticed increasing pain in both hips and recently knee pain."*

- Cross validation accuracy: 85%

- **Emotional needs:** *"I will have 6-8 months of chemo. I am so scared. I do not know what to expect. I am having a hard time dealing with this and am going to attend a support meeting in April. I having a difficult time staying positive and upbeat. I have read such amazing stories on here I hoping that this board will help me as well..((((HUGS TO ALL))))"*

- Cross-validation accuracy: 80%

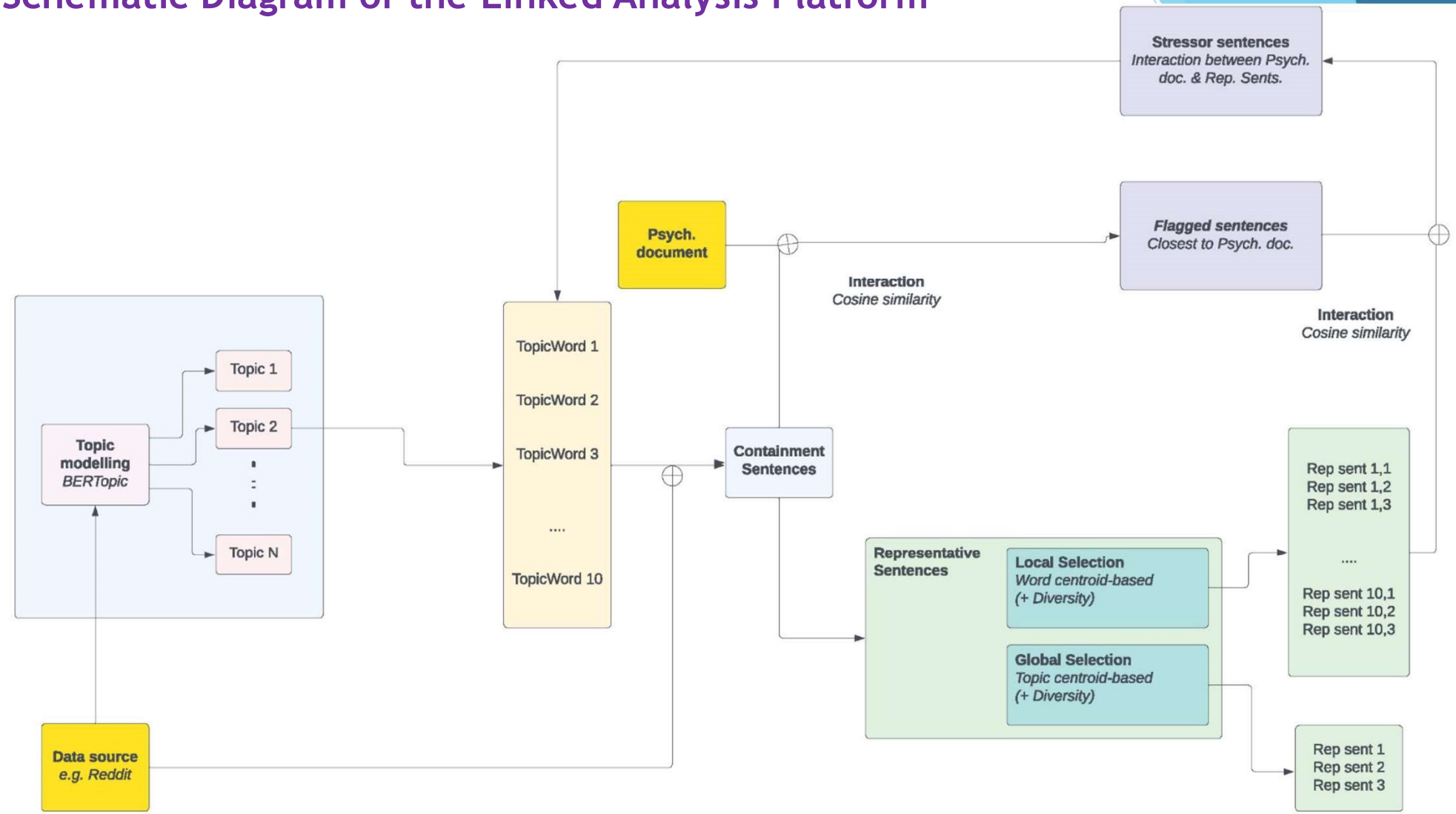
Another Use Case: Mental Health and Psychiatry

- Part 1, Clinical documents: in psychiatry, even clinical documents, e.g., psychiatric assessments, are highly unstructured
- Part 2, User generated content: social media posts
  - To monitor at-risk adolescents through their instant messaging content (because over 80% of all youths are heavy users of social media)
  - Develop a recommendation system for early intervention
- Dataset: 1,000 youths admitted to hospitals through emergency room due to self-harm: their admission notes, discharge summaries, and their social media posts 6 months prior to admissions
- One predictive model we are building: identify high-risk re-admission cases

A Platform for Online Psychiatric Analysis on Social Media Posts

- A Health Canada funded project to monitor the mental health of university students across Canada, eg., UBC, U of Toronto, etc.
- Enrolled 35,000 university students across Canada
- UBC students alone generated 300,000+ Reddit posts between 2020 and 2022
- Selected questions of interest:
  - What do they talk about?
  - What stress them out?
  - How does specific stress change over time?
  - How does specific stress differ across campuses/locations?

Schematic Diagram of the Linked Analysis Platform



Two Final Remarks

- Multi-lingual issue
  - Most NLP research driven by English corpora
  - One way to try a different language X is by automatic translation of documents in X to English, and apply the English models
  - A longer-term way is to apply transfer learning to English large language models to build models from documents in language X
- Even though we talk about written text so far, what about speech
  - Huge amounts of data collected by speech technologies, e.g., Siri for Apple, Alexa for Amazon
  - One way is to automatically transcribe speech to text and apply NLP-based models

Thank You!

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Future Work in Mental Health

- Adapt the model to monitor at-risk adolescents through their instant messaging content (because over 80% of all youths are heavy users of social media)
  - Develop a recommendation system for early intervention
- Apply transfer learning to build models for other populations:
  - Cancer patients
  - Patients with serious chronic conditions who stay at home
  - Seniors
  - Isolated individuals, e.g., covid-19