EEP 596: AI and Health Care || Lecture 10

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May 2, 2022

Logistics

- Mini Project 1 first deadline - Sunday, May 1

Logistics

- Mini Project 1 first deadline - Sunday, May 1
- Mini Project 1 second deadline - Friday, May 6

Final

Logistics

- Mini Project 1 first deadline - Sunday, May 1
- Mini Project 1 second deadline - Friday, May 6 Anything else?

(Sunday)

Last Lecture

1. Cancer Study
2. Cancer Diagnosis
3. AI Methods for Cancer Diagnosis

Today's Lecture

1. Handwriting recognition
2. Automated scribing from notes or audio

OCR - MNIST Data Set

ICE #0

ML Problem Type

Digit recognition on the MNIST Data Set can be modeled as which "ML Problem Type"

1. Unsupervised Learning
2. Binary Classification
3. Multi-class classification
4. Multi-label classification

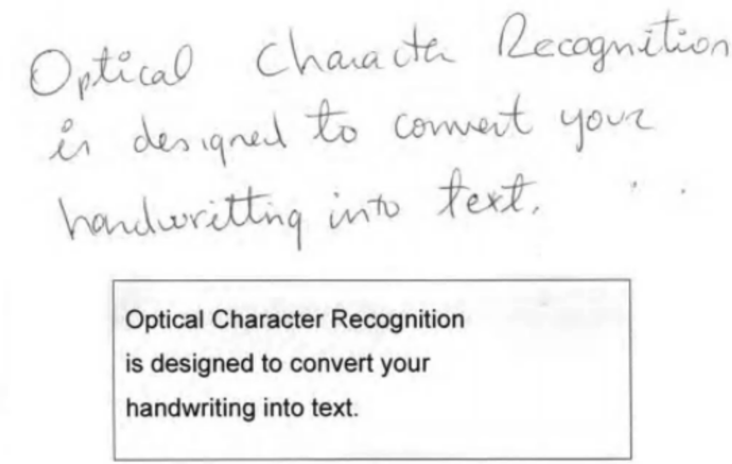
ICE #1

ML Methods for MNIST

Which ML method would you use for the MNIST data set to recognize digits?

1. K-means++
2. LSTM
3. CNN
4. SVM

OCR


Optical Character Recognition
is designed to convert your
handwriting into text.

OCR Solved?

OCR Tech

OCR tech has been around for a while. It's considered a solved problem for "clearly written text".

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Classic use-case for this?

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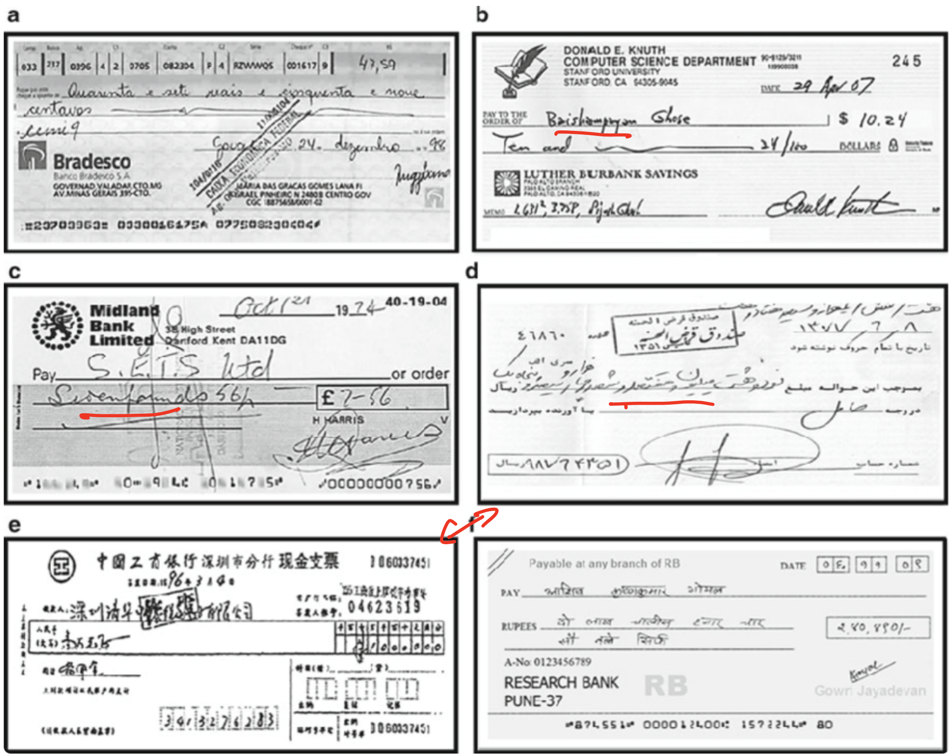
Classic use-case for this?

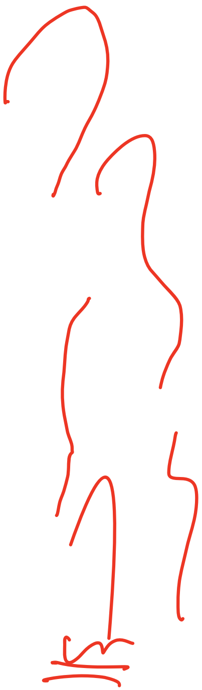
Doctor's handwriting!!

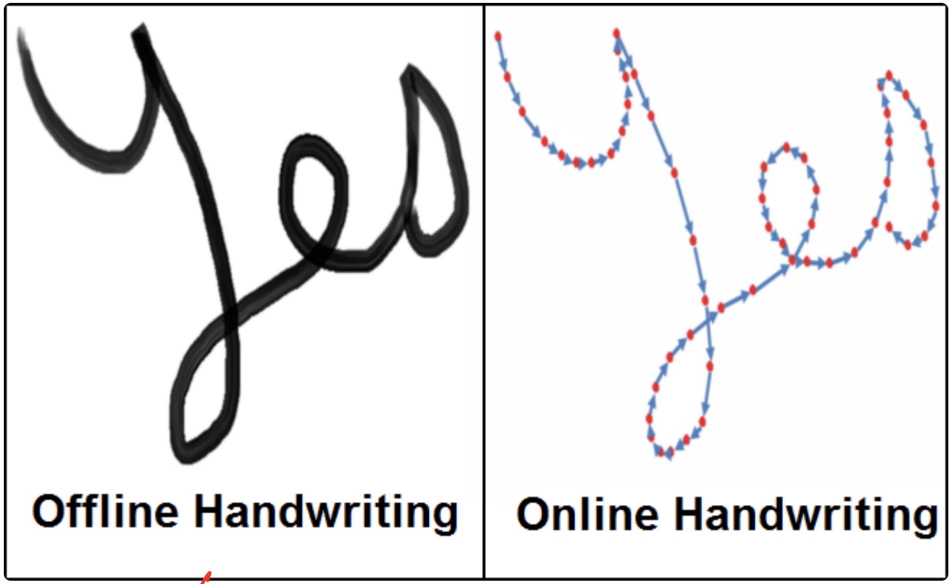
Use case: Banking



Source :- https://www.researchgate.net/figure/mages-of-handwritten-bank-cheques-from-different-countries-a-Brazilian-1-b-American_fig2_226705617

Offline vs Online Handwriting recognition

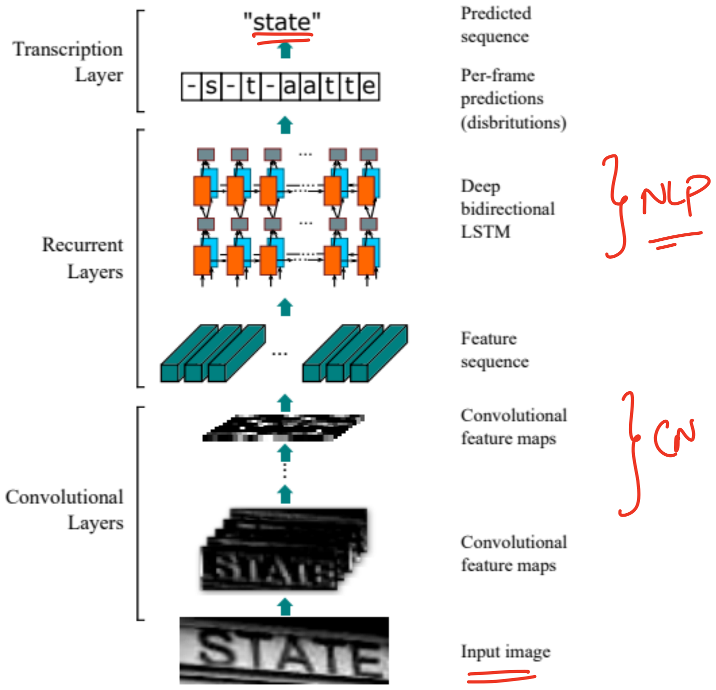




scenario!

Healthcare

Deep Learning for OCR



Motivation for Digital Scribe in a clinical context

1. Taking notes associated with clinician burnout

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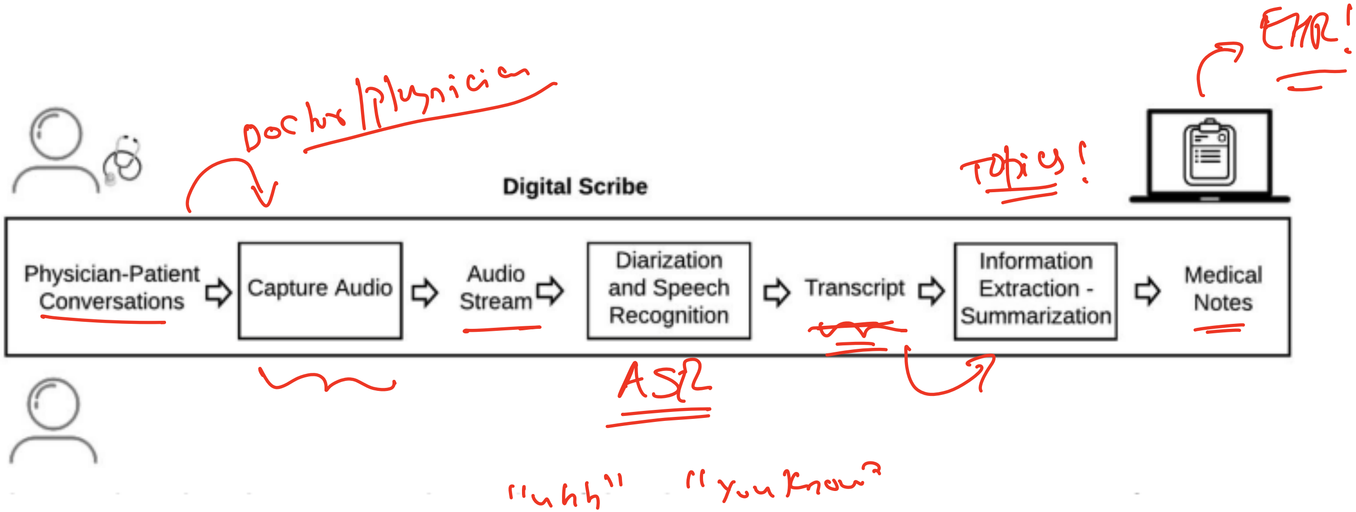
Motivation for Digital Scribe in a clinical context

1. Taking notes associated with clinician burnout
2. Information loss and distractions
3. Lost time from the primary tasks
4. DeepScribe

Ideal Digital Scribe



Challenges in Digital Scribing

ML problems

Table 1. The challenges associated with the various tasks a digital scribe must perform.

Task	Challenge
Recording audio	• High ambient noise
	• Microphone fidelity
	• Multiple speakers
	• Microphone positioning relative to clinician and patient
Automatic speech recognition (ASR)	• Varying audio quality
	• High ambient noise
	• Multiple speakers
	• Disfluencies, false starts, interruptions, non-lexical pauses
	• Complexity of medical vocabulary
	• Variable speaker volume due to distance to microphone and relative positioning
	• Differentiating multiple speakers in the audio (speaker diarization)
Topic segmentation	• Unstructured conversations
	• Non-linear progression of topics during a medical conversation
Medical concept extraction	• Noisy output of programs mapping text to UMLS → univ medical Language system?
	• Tuning of parameters of tools used to map text to UMLS
	• Contextual inference (understanding the appropriate meaning of a word or phrase given the context)
	• Phenomena in spontaneous speech such as zero anaphora, thinking aloud, topic drift
Summarization	• Summarization of non-verbal unstructured communication
	• Integrating medical knowledge to identify relevant information
	• Contextual inference
	• Resolving conflicting information from the patient
	• Updating hypotheses as the patient discloses more information
	• Generating summaries to train a summarization ML model
Data collection	• Clinician and patient privacy concerns
	• Costly data collection and labeling
	• Patient consent to be audio recorded and use the data for research purposes
	• De-identification and anonymization of data
	• Expensive datasets
	• Data held privately as an intellectual property asset
	• Clinician reluctance to be recorded due to fear of legal liabilities and extra workload

Challenges in Digital Scribing

Input

Dr: Do you drink alcohol?
Pt: Occasionally.
Dr: Like every week or two
Pt: Every two weeks.
Dr: Ok [pause] Alright and Family history, mum and dad are they alive and well and healthy?

Social History

Family History

Topic Segmentation Problem

Dr: So, when you're hungry it feels uncomfortable. Have you had that before or is this all new, do you think?
Pt: I think last year I used to have that but then I have some medicine to reduce the acid level and then it improved. Yeah.
Dr: Is that something that was prescribed in Australia?

Present Complaint

Drug History

NER

Intent Classification

[The patient steps on the scale.]
Dr: So, you haven't lost a whole lot of weight?
Pt: It doesn't show already. Do I have to press any buttons?
Dr: Ah, yes. Step off. Fifty-four point three.
[The patient steps off the scale.]
Pt: So, already one kilo decrease.
Dr: Okay. One kilo less?
Pt: Yeah.
Dr: Any blood in the bowel motions or vomiting blood, nothing like that?
Pt: No, no.

Physical Examination

Summarization

Present Complaint

Fig. 2 Three examples of transitions of clinician–patient conversations lacking clear boundaries and structure. Medical conversation fragments are on the left and the respective topics are on the right. Medical conversations do not appear to follow a classic linear model of defined information seeking activities. The nonlinearity of activities requires digital scribes to link disparate information fragments, merge their content, and abstract coherent information summaries.

Next Lecture

1. DL for OCR
2. NLP methods for extracting topic segmentation Summarization and generating an automated and structured EHR

References

1. Challenges of developing a digital scribe to reduce clinical documentation burden. Nature, 2019.
2. Nice blog