Can we build diagnostic machines using automated Conversation Analysis?

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Automated CA & diagnostic decision making
Background

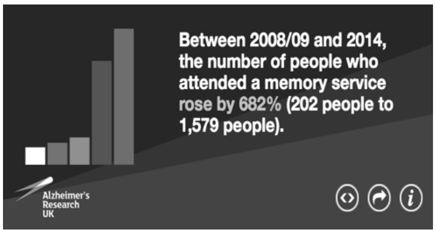
Typical diagnostic journey for patients with memory complaints

General Practice
- Patients complaining of memory problems in primary care may be referred for specialist evaluation

Within the memory clinic
- **History-taking by neurologist**
- Neuropsychological testing (potentially repeated)
- Brain scanning (MRI, CT, PET, potentially repeated)
- Diagnosis

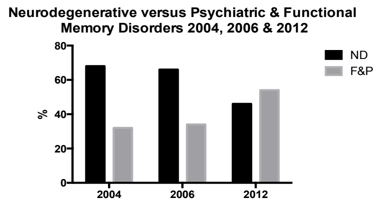
Automated CA & diagnostic decision making
Background

Increasing pressure on specialist memory services in the UK



Automated CA & diagnostic decision making
Background

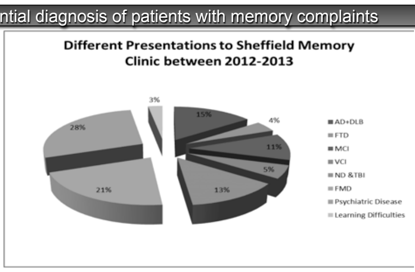
Increasing proportion of FMD presentations in UK memory clinics



Blackburn, D. J., et al. Memory difficulties are not always a sign of incipient dementia: a review of the possible causes of loss of memory efficiency. *Brit med bulletin* 2014:112:71–81.

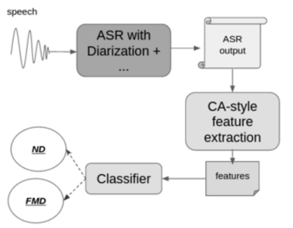
Automated CA & diagnostic decision making
Background

Differential diagnosis of patients with memory complaints



Automated CA & diagnostic decision making
Overview

Proposed solution: Automated screening / diagnostic stratification



- ASR: Automatic Speech Recognition
- ND: Neurodegenerative Memory Disorder
- FMD: Functional Memory Disorder

Automated CA & diagnostic decision making
Overview

Development of an automated diagnostic decision aid

1. CA study of “natural” memory clinic interactions.
2. CA-inspired automatic analysis of manually produced transcripts of “natural” interactions.
3. CA study of “natural” clinic versus Intelligent Virtual Agent (IVA) interactions
4. CA-inspired automatic analysis of automatically produced transcripts.
5. Optimisation of CA-inspired automatic analysis by combination with other diagnostic methods.

Automated CA & diagnostic decision making
1. CA study of “natural” memory clinic interactions

Aim and methods

- **Aim:**
- To identify features in patients’ talk which could help distinguish between neurodegenerative and functional memory disorders.

- **Method:**
- Audio- / video recording of new appointments in the memory clinic (n=105).
- Medical “gold standard diagnoses”
- Description of conversational profiles of NDD (n=15) and FMD (n=15).
- Blinded multirater prospective testing of diagnostic potential conversational profiles (n=10).

Automated CA & diagnostic decision making
1. CA study of “natural” memory clinic interactions

Results

Quantitative findings (15 FMD vs 15 ND patients)

Item	Description	A: Typical of ND	B: Typical of FMD	No. ND Cases Categorized A/B (n = 15)†	No. FMD Cases Categorized A/B (n = 15)†	Difference ND vs. FMD (*P*)
A						
1	Is the patient accompanied	Yes	No	14/1	6/9	0.003
2	Who is most concerned?	Others	Patient themselves	6/1	0/9	0.0008
3	Specific example of memory failure	No or partial/incomplete answer or offers a general/routine problem	Detailed and specific response about a recent occurrence	11/0	1/11	< 0.0001
4	Ability to recall recent episodic memory during interaction	Patient unable to recall earlier talk	Patient able to recall earlier talk (like I said)	11/3	0/8	0.001
5	Responding to compound questions	Unable to attend to different parts of compound questions	Can attend to different parts of compound questions	7/1	3/7	0.02
6	Prevalence of “I don’t know” verbal responses	Indicates recall-based problems	Response to unexpected questions	11/1	1/14	< 0.0001
7	Patients’ elaborations and length of turns	Short, “literal” answers	Long responses, that provide extra detail	9/6	0/11	0.002
8	Repetition	More frequent	Less frequent	10/3	1/11	0.001
9	Production of talk	Struggle to reply to questions, communication difficulties	Able to provide answers when asked	7/2	1/13	0.001

Reuber, M. et al. An interactional profile to assist the differential diagnosis of neurodegenerative and functional memory disorders. Alzheimer Dis Assoc Disord 2018;32:197–206.

Automated CA & diagnostic decision making
1. CA study of “natural” memory clinic interactions

Results

Quantitative findings in accompanied patients (6 FMD vs 14 ND patients)

Item	Description	A: Typical of ND	B: Typical of FMD	No. ND Cases Categorized A/B (n = 14)	No. FMD Cases Categorized A/B (n = 6)	Difference ND vs. FMD (*P*)
B						
10	Main interactional contribution/ role of the AP	AP acts as patient’s representative or spokesperson	AP’s role limited to confirmation checks and second opinions	9/1	1/5 (n = 6)	0.008
11	Presence of head-turning sign (excluding verbal “I don’t know” replies)	Patient defers answering to AP by turning to them	Able to answer most questions, turn for confirmation only	10/4	3/3	NS
12	Disagreements between patient and AP	Present	Not present	13/1	2/4	NS
13	Word searches	Displays “word search” difficulties during consultation, AP provides “missing” information	Report “word search” difficulties in the past but does not display “word search”	3/1	3/3	NS
14	Responding to personal questions	Evidence of difficulties answering these questions	Can answer these questions relatively easily	6/5	0/6	NS

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Automated CA & diagnostic decision making
1. CA study of “natural” memory clinic interactions

Differential diagnostic findings

- 15+5 patients with neurodegenerative memory disorder, 15+5 patients with functional memory disorder
- Phase 1: Evaluation of Diagnostic Scoring Aid (15+15)
- Phase 2: Prospective pilot trial of DSA (5+5 patients, 2 raters)
- Phase 1: Median DSA score NMD +5, FMD -5 (p<0.001), optimal diagnostic cutoff: +1, sensitivity 86.7%, specificity 100%, interrater agreement: Kappa 0.8.
- Phase 2: Rater 1: correct 10/10, rater 2: 9/10

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Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

Aim and methods

- **Aim:**
- To explore whether a range of acoustic, syntactic, semantic and visual features inspired by CA findings can be defined in a computer-readable format, extracted automatically from transcripts and fed into an automatic classifier to automate the differentiation of conversational patterns typical of ND and FMD.

- **Method:**
- 30 audio-recordings and manual transcripts of new appointments in the memory clinic (15 patients with FMD, 15 with ND).
- Medical “gold standard diagnoses”.
- Computer readable feature definition inspired by CA findings.
- Automatic classification with range of classifiers (leave-one-out method).

Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

”Translation” of CA findings into computer-readable features

Diagnostic profiling characteristic (Elsey *et al.*)	Proposed, automatic feature(s)
F1) Accompanying person (role of)	number of turns (**1.APsNoOfTurns**[a], **2.PatNoOfTurns**[a]); average length of turn ([sec]) (**3.APsAVTurnLength**[a], **4.PatAVTurnLength**[a]); average unique words in a turn (**5.APsAVUniqueWords**[b], **6.PatAVUniqueWords**[b])
F2) Responding to neurologists' questions about memory problems	patient answered "me" (**7.PatMeForWhoConcerns**[c])
F3) Patient recall of recent memory failure	number of empty words (**8.PatFailureExampleEmptyWords**[c]); average length of pauses (**9.PatFailureExampleAVPauses**[a]); used all the time (**10.PatFailureExampleAllTime**[c])
F4) Responding to compound questions	patient replies 'dunno for the expectation question (**11.PatDunnoForExcpectations**[c]); how many times 'dunno' in combination with turning to AP (**12.PatAVNoOfDunno**[d]); average number of shaking head (**13.PatAVNoOfShakesHead**[d]); average number of filler words (**14.PatAVFillers**[c]); average number of empty words (**15.PatAVEmptyWords**[c]); average number of low-frequency words (**16.PatAVAllWords**[b])
F5) Inability to answer	average number of repeated questions (**17.AVNoOfRepeatedQuestions**[c])
F6) Patient's elaborations and length of turn	patients average unique words in a turn (**6.PatAVUniqueWords**[b], **4.PatAVTurnLength**[a])
Features not in Elsey *et al.* but relating to neurologists role	number of turns (**18.NeuNoOfTurns**[a]); length of turns([sec]) (**19.NeuAVTurnLength**[a]); average number of unique words (**20.NeuAVUniqueWords**[b]); average number of topics discussed (**21.AVNoOfTopicsChanged**[c]); average length of pauses by patient (**22.PatAVPauses**[a])

B. Mirheidari, D. Blackburn, M. Reuber, T. Walker, and H. Christensen. Diagnosing people with dementia using automatic conversation analysis,"in Proceedings of Interspeech , pp. 1220{1224, ISCA, 2016.

Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

Computer-readable feature types

Type	Features
Acoustic	APsNoOfTurns PatNoOfTurns NeuNoOfTurns APsAVTurnLength PatAVTurnLength NeuAVTurnLength PatAVPauses
Lexical	PatAVUniqueWords NeuAVUniqueWords APsAVUniqueWords PatAVAllWords
Semantic	PatMeForWhoConcerns PatFailureExampleEmptyWords PatFailureExampleAllTime PatDontKnowForExpectation PatAVFillers PatAVEmptyWords AVNoOfRepeatedQuestions AVNoOfTopicsChanged
Visual-conceptual	PatAVNoOfShakesHead PatAVNoOfDontKnow

B Mirheidari, D Blackburn, K Harkness, T Walker, A Venneri, M Reuber, H Christensen. Toward the automation of diagnostic Conversation Analysis in patients with memory complaints. *J Alzheimer Dis* 2017;58(2),373-87.

Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

”Translation” of CA transcripts into computer-readable XML files

a) Manual CA

056 (dementia, accompanied)		
1	Neu	How's er:reading, writing, spelling?
2	Pat	Erm(.) <reading >(.) I read an awful lot(.) how- ever, I have-and the only
3		way I've noticed it is, well we've got a three year old grandson and I=
4	AP	=Oh yeah

b) Transcript file

```
(0:12:21.3) Neu: How's er reading, writing, spelling?
(0:12:28.1) Pat: Um, reading, I read an awful lot, however, I have, and the only
way I've noticed it is, well we've got a (laughs) three year old grandson and I.
Oth: Oh yeah.
```

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Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

”Translation” of CA transcripts into computer-readable XML files

c) XML file

```
1<?xml version='1.0'?>
2<conversations>
3     ...
4     <turn starttime="741.30" endtime="748.10"
          speaker="NEU056">
5         <phrase type="verbal">How's er reading,
              writing, spelling?</phrase>
6     </turn>
7     <turn starttime="748.10" endtime="759.50"
          speaker="PAT056">
8         <phrase type="verbal">Um, reading, I
             read an awful lot, however, I have,
              and the only way I've noticed it
             is, well we've got a</phrase>
9         <phrase type="others" value="LAUGHS"/>
10        <phrase type="verbal">three year old
             grandson and I.</phrase>
11    </turn>
12    <turn starttime="759.50" endtime="759.50"
          speaker= APS056">
13        <phrase type="verbal">Oh yeah.</phrase>
14    </turn>
15    ...
16</conversations>
```

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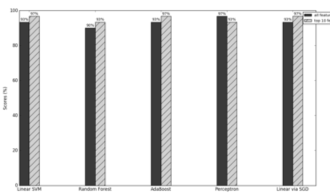
Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

Findings: Automatic classification accuracy ND versus FMD



Classifiers from Scikit-learn library:

- Support Vector Machine (SVM) with linear kernel
- Random Forest
- Adaptive Boost (Adaboost)
- Perceptron
- Stochastic Gradient Descent (SGD, linear classification)

Mean classification accuracy: 93%

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Automated CA & diagnostic decision making
2. Automatic CA of manually produced transcripts

Top 10 features used by different classifiers

Rank	Feature Name
1	NeuAVUniqueWords
2	APsNoOfTurns
3	PatAVUniqueWords
4	PatAVTurnLength
5	AVNoOfRepeatedQuestions
6	PatFailureExampleEmptyWords
7	PatAVFillers
8	PatAVAllWords
9	PatMeForWhoConcerns
10	PatAVPauses

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Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Aim and methods

- **Aim:**
- To explore whether patients with memory complaints are able to interact with an intelligent virtual agent (IVA) and that IVA-patient interactions continue to demonstrate differences between ND and FMD interactions.

- **Method:**
- Video/audio-recordings and manual transcripts of new appointments in the memory clinic & IVA-patient interactions.
- Medical "gold standard diagnoses".
- Conversation analytic examination and comparison of both types of interactions.
- 12 Memory clinic vs 10 avatar interactions (11 patients with FMD, 11 with ND).

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Intelligent Virtual Agent (IVA, early version)

Prototype avatar (using https://www.botlibre.com).

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Interaction with IVA ("digital doctor")

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

IVA script

"Hello I am a computerised doctor and I will be asking you questions today. I will ask you the sort of questions doctors ask in the memory clinic. Thank you for talking to me. I will start to ask you questions shortly.

1. Where have you come from today, and what are you are hoping to | find out?"

2. Tell me what problems you have noticed with your memory recently

3. Who is most worried about your memory, you or somebody else?

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

IVA script

4. What did you do over last weekend, giving as much detail as you can?

5. What has been in the news recently?

6. Tell me about the school you went to and how old were when you left.

7. Tell me about your last job? Give as much detail as you can.

8. Who manages your finances? you or somebody else? Has this changed recently?

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Findings: Doctor's questions are much more variable than IVA's

(1) 056: DR-ND

```
→ Neu:   okay ((pause)) and- (.) could you give me an example of the
         last time your memory let you down
         (0.3)
  Pat:   no (1.0) no (1.0) can you ((turns to partner))
```

(2) 036: DR-FMD

```
→ Neu:   um (1.4) when: (0.4) can you give me an example of the last
         time your memory let you sa- let you down
         (1.0)
  Pat:   .hhhhh i- m- erm:: (0.5) I was on the telephone (0.8) making an
         appointment for someone at wor:k .hh and we send appointment
         cards out to 'em .hh and I picked the appointment card up and I
         said to the- (.) customer .hh right I will send you a and I
         couldn't think (0.9) of the word appointment ca(h)rd
         ((laughs))=
```

Walker T et al. Developing an intelligent virtual agent to stratify people with cognitive complaints: A comparison of human–patient and intelligent virtual agent–patient interaction. Dementia 2018;DOIDOI: 10.1177/1471301218795238.

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Findings: Doctor's questions are much more variable than IVA's

(3) 083: DR-ND

→ Neu: and cn- can you tell: m:e=give me examples of how your memory
has let you down
(2.3)
Pat: I find it- I find it very easy to forget things these days

(4) 043: DR-ND

→ Neu: okay. An:d are there any kind of specific things that you can
→ think of that- th'kind of (.) typical memory problems that you
→ were having at that time
(0.4)
Oth: I don't know (now)=
Pat: =I can't remember ((la[ughs))

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Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Findings: Patients' responses to IVA similar to responses to doctor

IVA: "Tell me, what problems have you had with your memory."

(9) P03: IVA-FMD

Pat: ah various problem:s (1.2) with my memory .hhhhhh erm: m-s- a
lot of the ti:me I don't **remember** (0.3) what- .hhhhh (0.3) I've
got up to do: hhhhh erm .hhhhh go shomewhere:: (0.6) get there:
don't know what I've gone for (1.7) erm (1.0 can't **remember**
wor:d:s (1.0) can usually **remember** the er (0.5) the letter they
start with .hhhhhh (0.4) but not the words
1 minute 19 seconds omitted, giving additional examples
but yeah it happens a lot

(10) P13: IVA-ND

Pat: u:m (2.6) a loss of um (2.8) **remembering** things at times (0.4)
words (.) different places (10.2) words and different places
just re- just remembering (1.5) remembering things at time
(0.4) not easy

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Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Findings: Start of IVA interaction (FMD, second IVA interaction)

Q2: (5 seconds) Yeah, this is recording now. (2 seconds) This is recording, there we
go. This one, and press enter to start.
Q1: Why have you come in today (1.0) and what (0.5) are your expectations
(0.7)
Pat: .hh I came in for a review one year after having er (.) problems with my
confidence due to stress (0.6) coming in: I was expecting:: that as all seemed
OK: I would probably be discharged
Q1: Tell me (0.7) what problems (0.6) have you had (0.7) with your memory
Pat: (2.3) My problems weren't actually with memory it was my confidence (.) an::d I
was making assumptions: when I was right (0.4) that in fact (.) I had made
mistakes I had forgotten to do something (0.5) er:: so: I was misidentifying it
as memory.

Automated CA & diagnostic decision making
3. CA analysis: doctor-patient vs. IVA-patient interactions

Findings: Start of avatar interaction (ND)

Q2: OK (0.4) Like I said (0.5) talk to the screen
Pat: Right.
Q2: (0.5)Forward (0.7) repeat (1.1) you may now begin
Pat: (0.2) Ri:ght. (2.7) That, I press that, don't I?
Q2: (0.2) Mm hmm [rising]
Q1: (0.5) ((click)) Why have you come in today (1.0)[and what (0.5)
Pat: [Why:-
Q1: [are your expectations
Pat: [why have I come in today
Pat: (.)((click))(0.6) Ri:ght. (3.2) I've forgot now (0.2) (laughs) I've come in
(0.8) to do: er: (0.8) to be a volunteer for rese:arch (2.8) Press this (0.2)
repeat one now?
Q2: Mm hmm
Q1: (1.0) ((click)) Why have you come in today (1.0) and what (0.5) are your
expectations
Pat: (2.0) I've come in today: (1.4) to help do a research programme (1.3) and my
expectations are: (0.7) to find out what's really wrong with me, if anything.
(1.8) Go to forward now
Q2: (0.9)Mm hmm.
Q1: (1.2) ((click))Tell me (0.7) what problems (0.6) have you had
Pat: (2.0) U:m (2.6) a loss of um (2.8) remembering things at times (0.4) words (.)
different places (10.2) words and different places (quietly) just re- just
remembering (1.5) remembering things at times (0.4) not easy (1.7) This one
again? (1.8) Is it this one again, repea:t one

Automated CA & diagnostic decision making
4. Automatic analysis of automatically produced transcripts

Aim and methods

- **Aim:**
- To provide proof-of-principle that interactions between and IVA and patients with memory problems can be transcribed using automatic diarisation and speech recognition (ASR), analysed by automated diagnostic features extraction and classified into ND and FMD groups.

- **Method:**
- Video/audio-recordings and automatic transcripts of IVA-patient interactions (plus 30 recordings / manual transcripts of doctor-patient interactions).
- Medical "gold standard diagnoses".
- Automatic diarisation, feature extraction and classification.
- Classification of 12 avatar interactions (6 patients with FMD, 6 with ND).

Automated CA & diagnostic decision making
4. Automatic analysis of automatically produced transcripts

Automatically extracted diagnostic features

Category	Feature
CA inspired	number of turns (**APsNoOfTurns**, **PatNoOfTurns**, **NeuNoOfTurns**); average length of turn (**APsAVTurnLength**, **PatAVTurnLength**, **NeuAVTurnLength**); number of unique words in a turn (**APsAVUniqueWords**, **PatAVUniqueWords**, **NeuAVUniqueWords**); patient answers "me" for question "who's most concerned" (**PatMeForWhoConcerns**); patient recalls memory failure features (**PatFailureExampleEmptyWords**, **PatFailureExampleAVPauses**, **PatFailureExampleAllTime**); patient replies 'dunno for the expectation question (**PatDunnoForExpectations**); average number of filler, empty, unique and low-frequency words (**PatAVFillers**), **PatAVEmptyWords**, **PatAVUniqueWords PatAVAllWords**); average number of repeated questions (**AVNoOfRepeatedQuestions**); average number of topics discussed (**AVNoOfTopics**)
Lexical (Part of speech)	average number of verbs, nouns, adjectives, adverbs, pronouns, wh_words(e.g, who), determiner, conjunctions, cardinals, existential(e.g., there is), prepositions etc(**PatAvgVerb**, **PatAvgNoun**, **PatAvgAdjective**, **PatAvgAdverb**, **PatAvgPronoun**, **PatAvgWh_word**, **PatAvgDeterminer**, **PatAvgConjunction**, **PatAvgCardinal**, **PatAvgExistential**, **PatAvgPreposition**, **PatAvgOtherPOS**)
Acoustic	average overall intonation, pitch, duration and silence(**PatAvgIntonation**, **PatAvgPitch**, **PatAvgDuration PatAvgSil**); difference between the first harmonic and the harmonic close to the first, second and third formants(**PatAvgH1-A1**, **PatAvgH1-A2**, **PatAvgH1-A3**); difference between the two first harmonics (**PatAvgH1-H2**); local jitter and shimmer(**PatAvgGitterLocal**, **PatAvgShimmerLocal**); harmonics-to-noise and noise-to-harmonics ratios(**PatAvgMeanHNR**, **PatAvgMeanNHR**)

Automated CA & diagnostic decision making
4. Automatic analysis of automatically produced transcripts

Findings: Automatically Speech Recognition accuracy

System	Train	Test	WER
Baseline_ HUM	HUM	HUM	55.7%
Baseline_AVA	AVA	AVA	77.0%
Cross domain	HUM	AVA	65.0%
MAP adaptation	Map on HUM	AVA	58.7%
Combining data	HUM+AVA	AVA	**46.2%**

(WER: Word Error Rate)

B. Mirheidari, D. Blackburn, K. Harkness, T. Walker, A. Venneri, M. Reuber, and H. Christensen, \An avatar-based system for identifying individuals likely to develop dementia," Proc. Interspeech 2017, pp 3147-3151.

Automated CA & diagnostic decision making
4. Automatic analysis of automatically produced transcripts

Findings: Automatic classification accuracy ND versus FMD

Train/Test	CA	AC	LX	ALL	T10
HUM_man/ HUM_man	**96.7**%	83.3%	66.7%	76.7%	**100**%
HUM/ HUM	**76.7**%	60.0%	50.0%	76.7%	**90.0**%
AVA_man+ HUM_man/AVA_man	58.3%	66.7%	**83.3**%	66.7%	75.0%
AVA_man+ HUM_man/AVA	72.7%	63.6%	63.6%	**81.8**%	72.7%
AVA+ HUM_man/AVA	63.6%	54.5%	63.6%	**90.9**%	72.7%

(' _man':using gold-standard transcript instead of ASR-produced transcripts; 'CA': Ca-style features; 'AC': acoustic features; 'LX': lexical features; 'T10': top 10 informative features.)

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Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Combination of method improvement and additional tools

- **Improvement of current method:**
- Better training of ASR using a much bigger data of situationally relevant data.
- Improvement of syntactic / semantic analysis by better automatic textual analysis (e.g. word vector representations such as 'w2vec'and 'GloVe' instead of 'bag of words' approach).
- Broader validation with other important diagnostic groups (depressed / healthy)

- **Additional tools:**
- Integration of previously standardised neuropsychological tests.
- Automatic acoustic analysis.
- Automatic video-analysis (eg. blinking / gaze / head turning behaviour).

Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Extension of IVA script

9. Please name as many animals as you can. You can name any type of animal. You will have one minute- please start after you hear the buzzer.

10. Please name as many words as you can that begin with the letter P. It can be any word beginning with P except for names or people such as Peter or names of countries such as Portugal. Please start answering after you hear the buzzer.

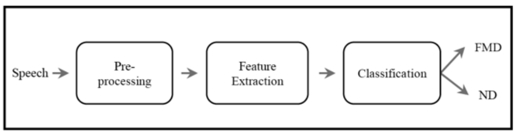
11. Tell me everything you see going on in this picture? Please describe it in as much detail as you can. When you have finished press FOREWARD.

Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Cookie theft picture

Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Method: Classification based on acoustic features



S. Al-Hameed, M. Benaissa, H. Christensen, B Mirheidari,D Blackburn,M Reuber. Using acoustic measures to assess cognitive interactional capability in patients presenting with memory problems. Manuscript in preparation 2018.

Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Method: Classification based on aucoustic features

Features	Type	Number of features
Fundamental frequency (F0) related measures (median, mean, STD, min and max)	Phonation and voice quality	5
Harmonic-to-noise ratio (HNR)	Phonation and voice quality	1
Number of pulses	Phonation and voice quality	1
Number, mean and STD of periods	Phonation and voice quality	3
Noise-to-harmonic ratio (NHR)	Phonation and voice quality	1
Shimmer scales	Phonation and voice quality	6
Jitter scales	Phonation and voice quality)	5
Autocorrelation	Phonation and voice quality	1
Fraction of locally unvoiced frames	Phonation and voice quality	1
Number of voice breaks	Phonation and voice quality	1
Degree of voice breaks	Phonation and voice quality	1
Number of turns	Phonation and voice quality	1
Average time of turns (include pauses)	Phonation and voice quality	1
Mel frequency cepstral coefficients (MFCC)	Spectral features: 42 features	(extended to 336)
Filter bank energy coefficient (Fbank)	Spectral features: 26 features	(extended to 224)
Mel frequency cepstral coefficients (MFCC)	Spectral features: 26 features	(extended to 224)
Total		812

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Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Preliminary findings: Classification based on aucoustic features

Classifier	All features (812) SVM wrapper (5)	Top(7) features based on on Pearson's Filter	Top (24) features based
Linear SVM	86.7 %	**96.7 %**	**96.7 %**
Random forest	73.30 %	93.3%	86.6%
Adaboost	86.6 %	**96.7%**	**96.7%**
MLP	70.00 %	**96.7%**	93.3%
Linear via SGD	76.7 %	**96.7 %**	93.3%
Mean	78.6 %	**96.0 %**	93.3%

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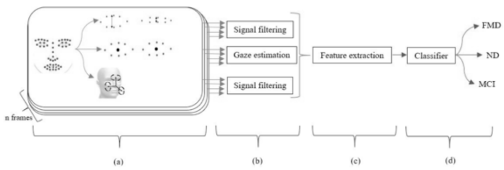
Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Method: Classification based on visual features



S. Al-Gawwam, M. Benaissa, Mirheidari, D. Blackburn, K. Reuber, H. Christensen. Visual features supporting the automatic identification of individuals likely to develop dementia. Manuscript in preparation 2018.

Automated CA & diagnostic decision making
5. Optimisation of automatic diagnostic procedure

Preliminary findings: Classification based on visual features

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
77.77	72.22	72.22	72.22	61.11	66.66	88.88	77.77

Table 1: Classification results for MCI vs NDvs FMD subjects using eye blink features

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
94.444	77.77	61.11	66.66	66.66	55.55	94.44	77.77

Table 2: Classification results for MCI vs NDvs FMD subjects using Head turning features

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
77.77	55.55	72.22	72.22	72.22	55.55	94.44	66.66

Table 3: Classification results for MCI vs NDvs FMD subjects using eye gaze features

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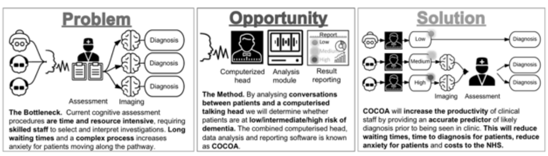
Automated CA & diagnostic decision making
The end

Diagnostic pathway of the future



Automated CA & diagnostic decision making
The End

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