Language Processing for Diagnosis and Prediction in Mental Health

Matthew Purver
Queen Mary University of London



with Niall Gunter, Christine Howes, Rose McCabe

Mental Health & Language

- Communication is important in mental health:
  - Communication quality associated with outcomes (e.g. Ong et al, 1995)
  - Communication *during treatment:*
    - Conversation structure (how) and content (what)

- Can NLP techniques help us analyse & understand therapy?

- PPAT project:
  - transcripts of face-to-face therapy for schizophrenia
- AOTD project:
  - online text-based therapy for depression & anxiety
- (Howes, McCabe, Purver, SIGDIAL 2012, IWCS 2013, ACL 2014)

- SLADE project:
  - transcripts of face-to-face diagnosis meetings for dementia

Questions

- What features of language correlate with / predict symptoms & outcomes?
  - Topic?
  - Sentiment/emotional content?
  - Specific words/phrases?

- Can we use them to help diagnosis and/or treatment?

- Can we detect them automatically?
  - Accurately
  - Robustly
  - Using existing NLP techniques/tools
- How can we do better?

PPAT: Face-to-Face Dialogue

- Transcripts of therapy for schizophrenia
- Manual annotation & statistical analysis
    - McCabe et al (2013)
- Automatic NLP processing & machine learning
    - Howes et al (2012; 2013)
- Detecting symptoms
    - *positive* (delusions, hallucinations, beliefs)
    - *negative* (withdrawal, blunted affect, alogia)
- Predicting related outcomes
    - ratings of communication quality
    - future adherence to treatment:
        - non-adherence: risk of relapse 3.7 times higher
    - shared understanding shown to be a related factor

Machine learning approaches

Unsupervised

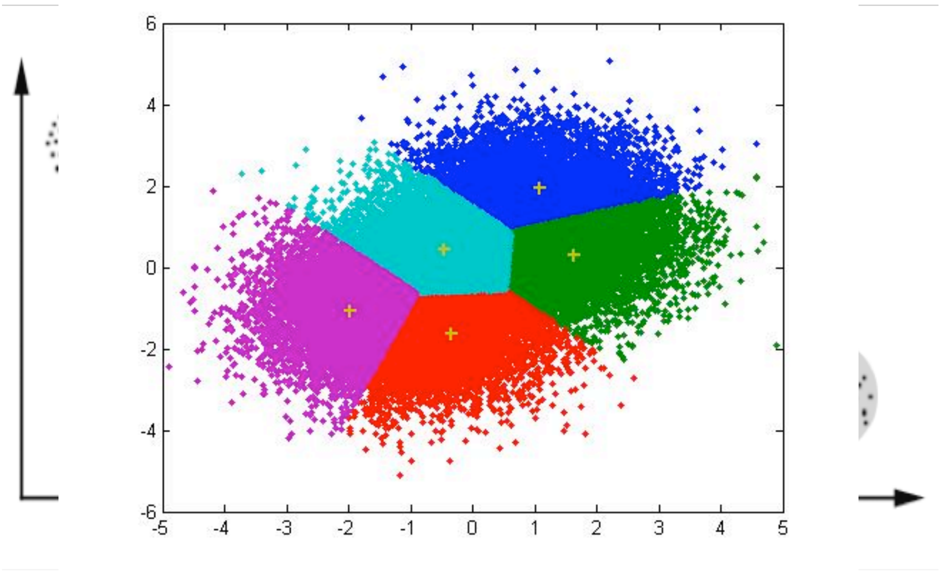
Uncover useful patterns without prior knowledge

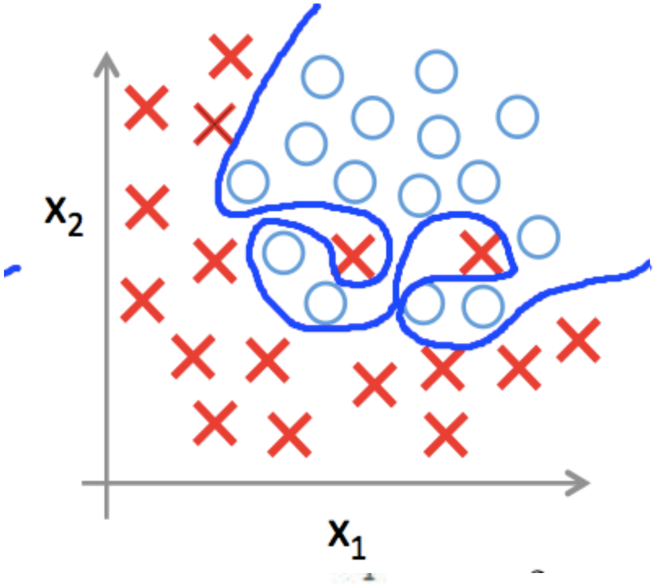
- Depend on data separability
- Depend on feature choice

Supervised

Learn from manually labelled examples

- Also depends on label choice, accuracy, reliability …





Images: wikipedia, coursera.com

NLP: brute force

- Classify entire dialogues (patient turns only) with SVMs, ngrams
  - Predict adherence to treatment 6 months later

Features	P (%)	R (%)	F (%)
Class of interest	28.9	100.0	**44.8**
Baseline features	27.0	51.9	**35.5**
Best ngram features	70.3	70.3	**70.3**

- Similar for symptoms, some outcomes e.g. HAS, PEQ
- Human psychiatrist given same task:

Data	P (%)	R (%)	F (%)
Text transcripts	60.3	79.6	**68.6**
Transcripts + video	69.6	88.6	**78.0**

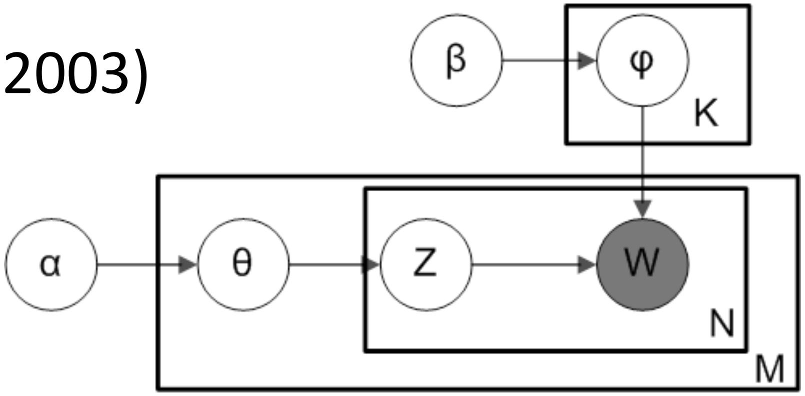
- But how well will this generalise? And what does it **mean**?

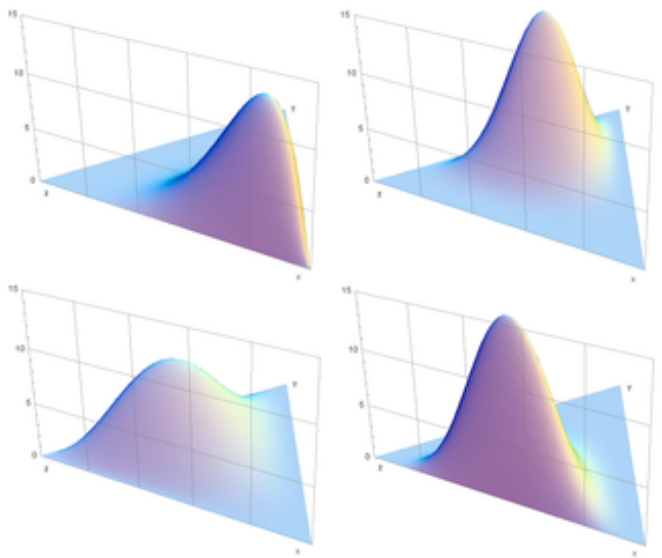
Manual topic segmentation

Topic	Name	Description
01	Medication	Any discussion of medication, excluding side effects
02	Medication side effects	Side effects of medication
03	Daily activities	Includes activities such as education, employment, household chores, dail
04	Living situation	The life situation of the patient, including housing, finances, benefits, plan
05	Psychotic symptoms	Discussion on symptoms of psychosis such as hallucinations and delusion
06	Physical health	Any discussion on general physical health, physical illnesses, operations,
07	Non-psychotic symptoms	Discussion of mood symptoms, anxiety, obsessions, compulsions, phobias
08	Suicide and self harm	Intent, attempts or thoughts of self harm or suicide (past and present)
09	Alcohol, drugs & smoking	Current or past use of alcohol, drugs or cigarettes and their harmful effect
10	Past illness	Discussion of past history of psychiatric illnesses, including previous adm
11	Mental health services	Care coordinator, community psychiatric nurse, social worker or home tre
12	Other services	Primary care services, social services, DVLA, employment agencies, polic
13	General chat	Includes introductions; general topics; weather; holidays; end of appointm
14	Explanation about illness	Patients diagnosis, including doctor explanations and patients questions ab
15	Coping strategies	Discussions around coping strategies that the patient is using or the doctor
16	Relapse indicators	Relapse indicators and relapse prevention, including early warning signs
17	Treatment	General and psychological treatments, advice on managing anxiety, buildi
18	Healthy lifestyle	Any advice on healthy lifestyle such as dietary advice, exercise, sleep hyg
19	Relationships	Family members, friends, girlfriends, neighbours, colleagues and relations
20	Other	Anything else. Includes e.g. humour, positive comments and non-specific

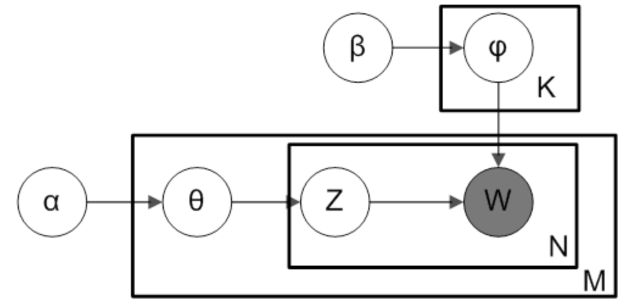
Topic Modelling

- Latent Dirichlet Allocation (Blei et al, 2003)
- Unsupervised Bayesian model:
  - texts as mixtures of "topics"
  - topics as distributions over words
- No prior knowledge of topics
  - number of topics
  - likely distribution shapes
  - (automatically optimised)
- Successful application in a wide range of domains & tasks





LDA topic modelling



- Infer 20 lexical “topics”:

Topic 0	feel low alright mood long drug feeling tired time confider
Topic 4	voices pills mood cannabis telly voice shaking chris contro
Topic 5	letter health advice letters council copy send dla cpn prob
Topic 7	church voice voices hear medication sister bad hearing tak
Topic 9	school children kids back september oclock gonna phone
Topic 10	weight months medication stone risk lose eat write gp has
Topic 11	place support work centre gotta job stress feel psychologis
Topic 12	door house police thought ring knew worse wall hadnt sat
Topic 13	doctor alright years nice ill anxious write long sit eye hear
Topic 14	drug taking milligrams hundred doctor night time medicat
Topic 15	sort medication work drugs kind team issues drink alcohol
Topic 16	mum place brother tablets died dad depot house meet mo
Topic 17	people life drug make care lot friends dry camera live cop
Topic 18	alright house drink drinking money alcohol god drugs livin

LDA topic modelling

- LDA topics given manual "interpretations":
  - (including sentiment aspect)

	Interpretation	Example words from top 20
0	Sectioning/crisis	hospital, police, locked
1	Physical health - side-effects of medication and other	gp, injection, operation
2	Non-medical services - liaising with other services	letter, dla, housing
3	Ranting - negative descriptions of lifestyle etc	bloody, cope, mental
4	Meaningful activities - social functioning	progress, work, friends
5	Making sense of psychosis	god, talking, reason
6	Sleep patterns	sleep, bed, night
7	Social stressors - other people stressors/helpful	home, thought, told
8	Physical symptoms - e.g. pain, hyperventilating	breathing, breathe, burning
9	Physical tests - Anxiety/stress arising from tests	blood, tests, stress
10	Psychotic symptoms - e.g. voices, etc.	voices, hearing, evil
11	Reasurrance/positive feedback/progress	sort, work, sense
12	Substance use - alcohol/drugs	drinking, alcohol, cannabis
13	Family/lifestyle	mum, brother, shopping
14	Non-psychotic symptoms - incl. mood, paranoia	feel, mood, depression

Manual vs LDA topic correlation

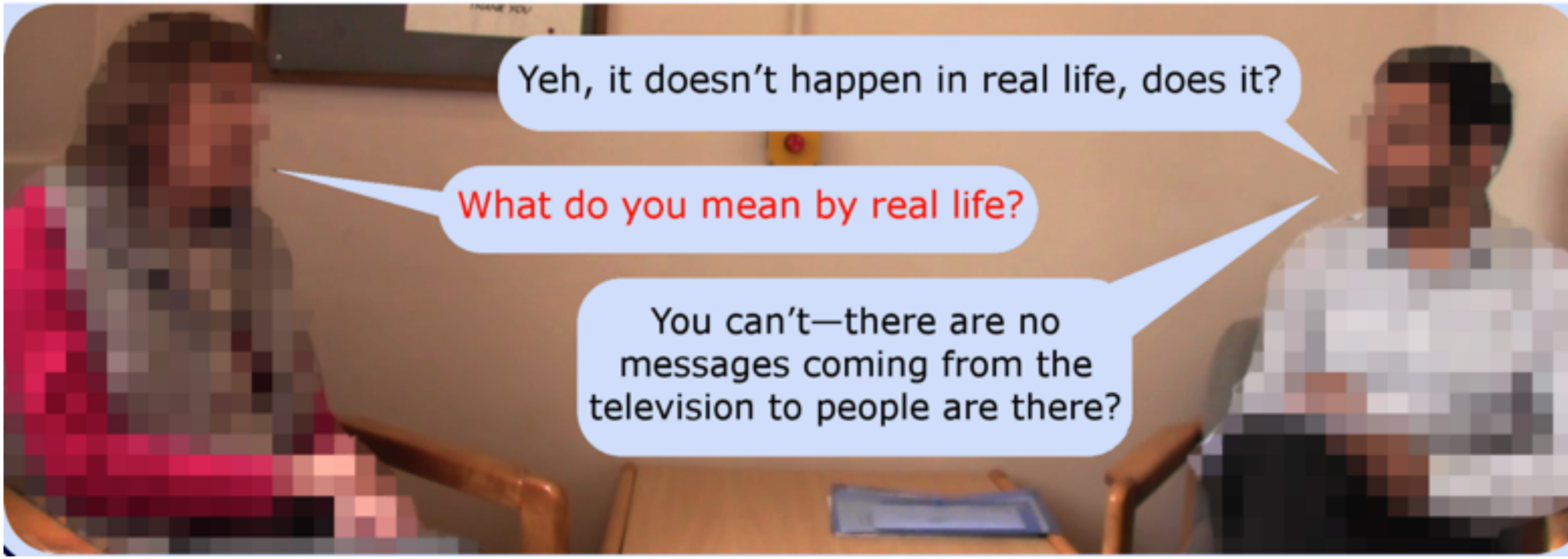
Hand-coded topic	Automatic topic	r	p
Medication	Medication regimen	0.643	<0.001
Psychotic symptoms	Making sense of psychosis	0.357	<0.001
Psychotic symptoms	Psychotic symptoms	0.503	<0.001
Physical health	Physical health	0.603	<0.001
Non-psychotic symptoms	Sleep patterns	0.376	<0.001
Suicide and self-harm	Weight management	0.386	<0.001
Alcohol, drugs and smoking	Substance use	0.651	<0.001
Mental health services	Non-medical services	0.396	<0.001
General chat	Sectioning/crisis	0.364	<0.001
Treatment	Medication issues	0.394	<0.001
Healthy lifestyle	Weight management	0.517	<0.001
Relationships	Ranting	0.391	<0.001
Relationships	Social stressors	0.418	<0.001
Relationships	Leisure	0.341	<0.001

Outcome prediction using topics

- Include topic weight per dialogue, with general Dr/P factors, as features:

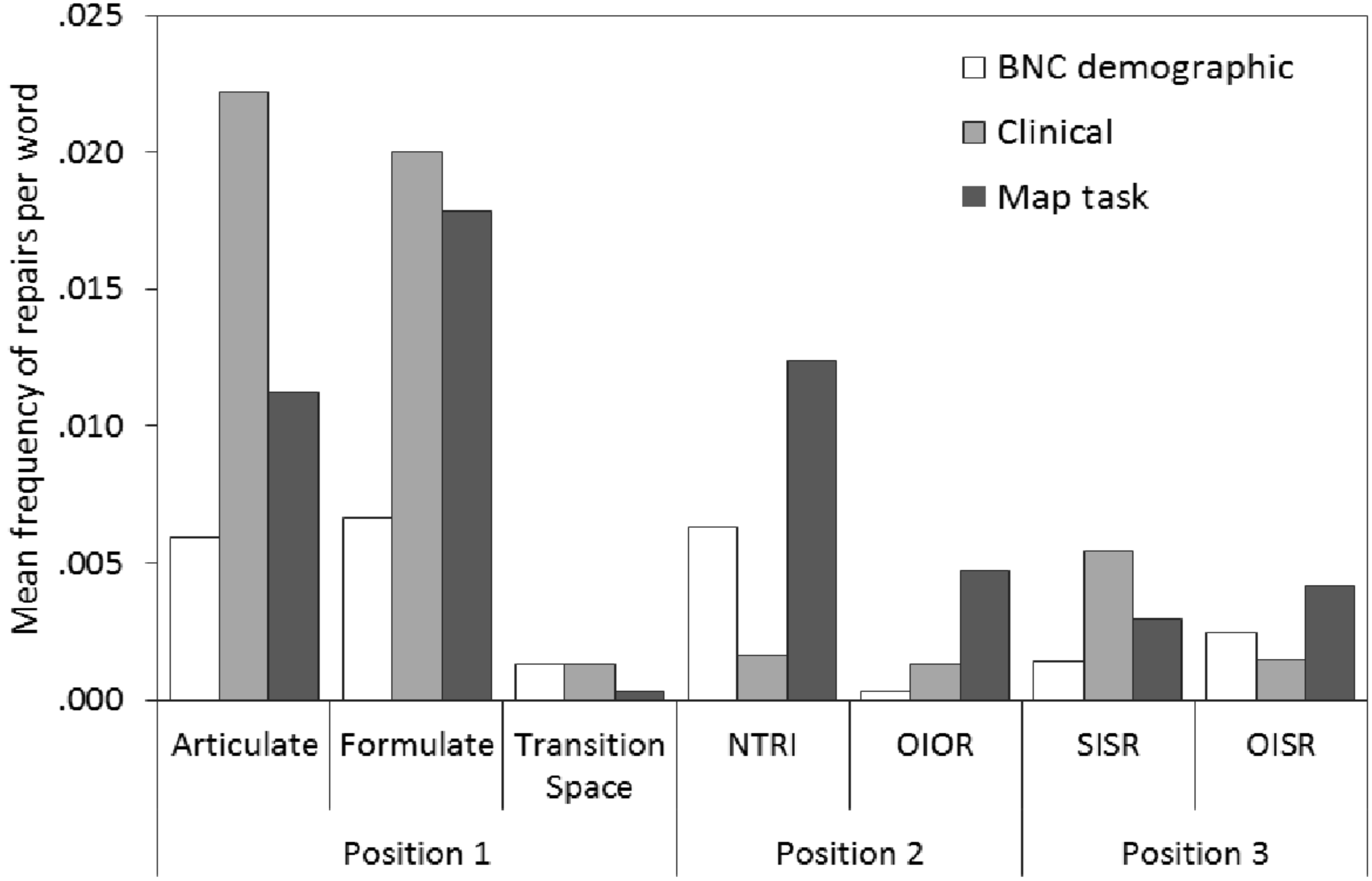
Measure	Manual Acc (%)	LDA Acc (%)
HAS Dr	**75.8**	**75.0**
HAS P	59.0	53.7
PANSS positive	**61.1**	58.8
PANSS negative	**62.1**	56.1
PANSS general	59.5	53.4
PEQ communication	59.7	56.7
PEQ comm barriers	**61.9**	**60.4**
PEQ emotion	57.5	57.5
Adherence (balanced)	**66.2**	54.1

Linguistic analysis: Repair



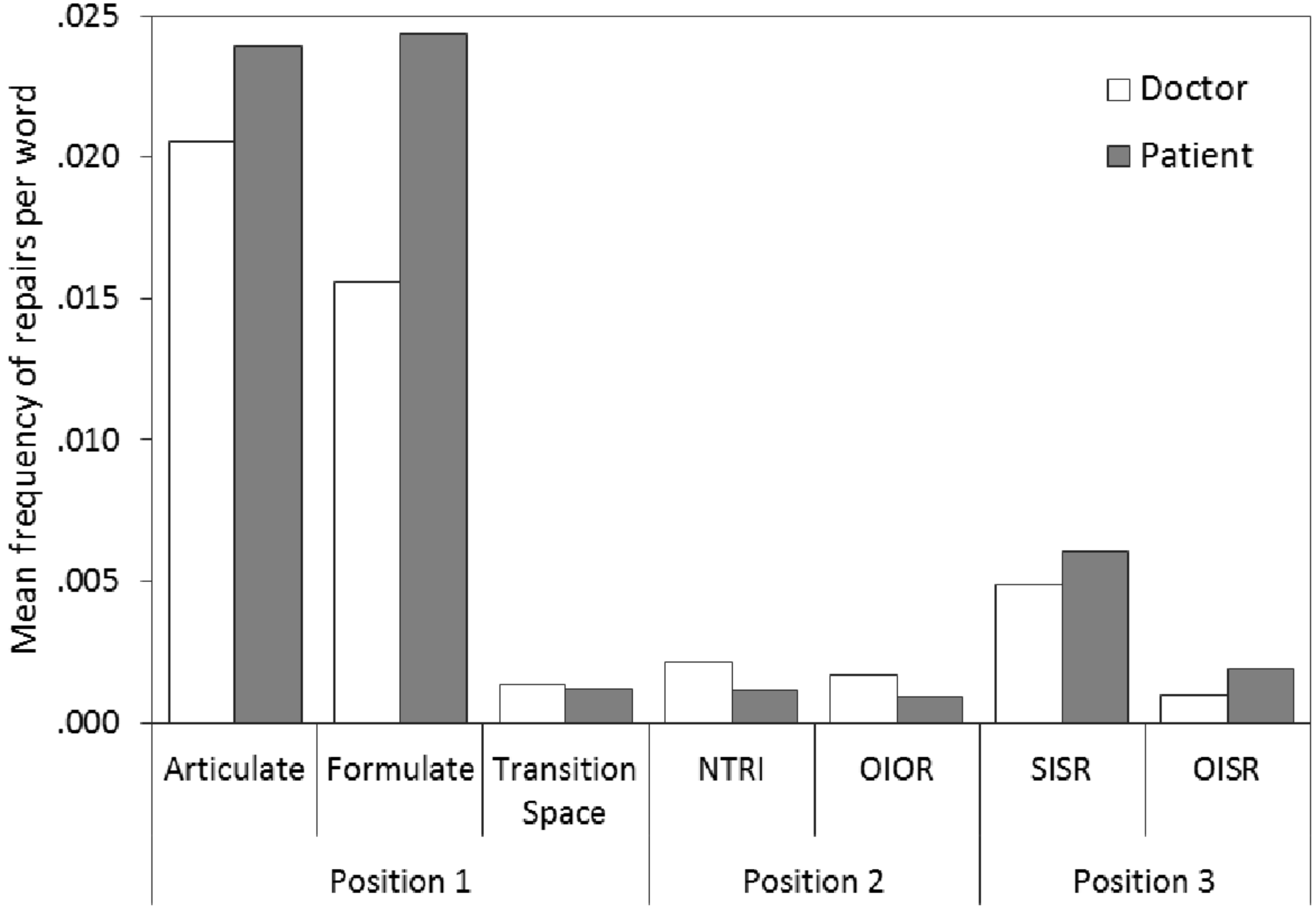
- Manual linguistic analysis
  - Significant role of *repair*
  - Patient-initiated other-repair & self-repair

Compare other dialogue contexts



- Therapy: more self-repair, less other-repair & initiation

Patient-doctor comparison



- Patients: more self-repair, less other-repair & initiation

Other-Repair

- Define features manually, extract automatically
  - Linguistically/observationally informed:
    - Wh-question words, closed class repair words
    - Repetition, parallelism
    - Backchannel behaviour, fillers, pauses, overlaps
  - Brute force: all unigrams
- Train SVMs to detect repairs (NTRIs & P2Rs)
  - 44,000 turns, only 567 NTRIs (159 patient), 830 P2Rs (262)
  - 80-86% on balanced data
  - but real data is unbalanced (only 1.3% NTRIs)
  - only 35-44% F-scores on real data (above 20-36% baselines)

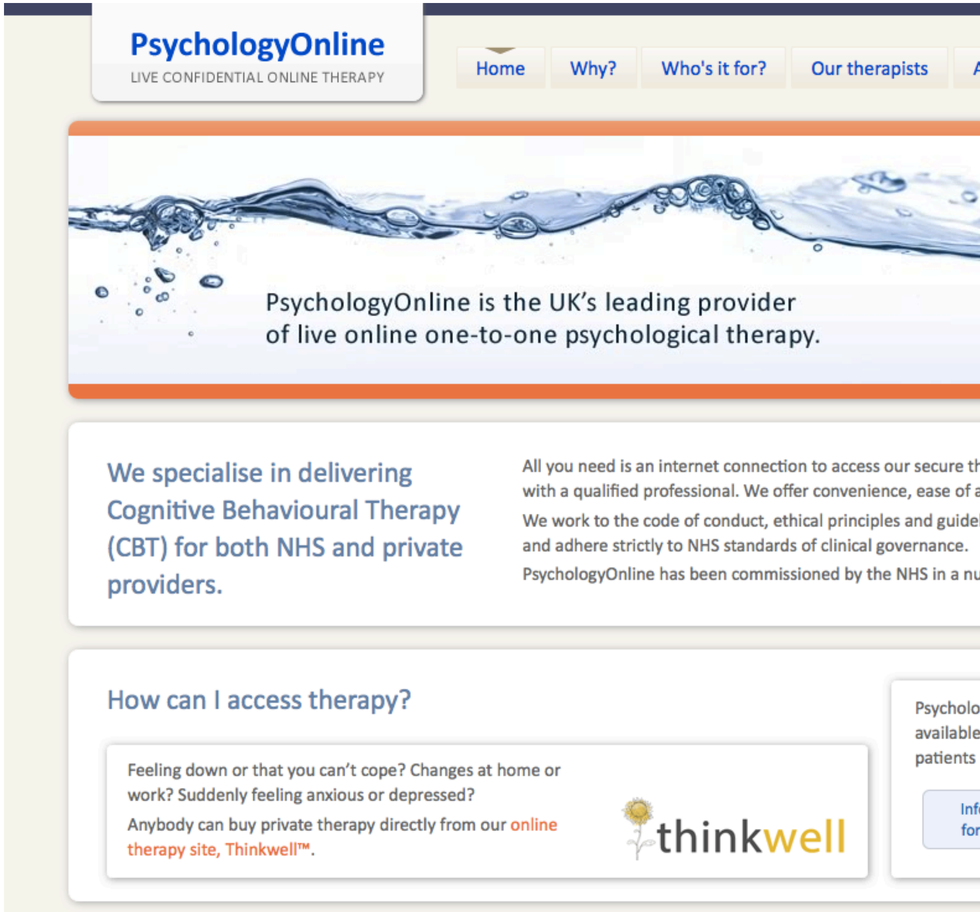
- We can do better
  - Semantic parallelism
  - Visual & audio features
  - … but it's not actually going to help (given this distribution).

Schizophrenia: Summary

- Repair correlates with adherence
  - automatic detection is difficult
  - … and it's a very sparse phenomenon
- Topic modelling provides useful features:
  - topics correlate well with human-annotated topics
  - topics predict symptom severity
  - topics predict therapeutic relationship ratings
  - topics & emotion/stance interrelate
- Predicting future adherence to treatment:
  - words & ngrams (phrases): 70%
  - humans: 70% (transcripts), 80% (video)
  - topics: 66% (manual), 54% (auto)
  - i.e. we can do it, but we don't really understand how …

Online Text-based Therapy

- Text-based therapy for depression & anxiety
  - PsychologyOnline Ltd
- Cognitive behavioural therapy
  - 2,000 sessions, 500 patients, mean 5.65 sessions/patient
- Anonymisation using RASP
  - (Briscoe et al, 2006)
  - Non-trivial
- Outcome measure
  - Patient Health Questionnaire (PHQ-9)
  - Current severity, progress since start



Patient Health Questionnaire (PHQ-9)

- Collected before each session
  - 0-27 scale: higher score = more severe depression
  - moderate/severe >=10 ***(in/out-of-caseness)***
  - Δ since start

PATIENT HEALTH QUESTIONNAIRE (PHQ-9)

NAME:________________________ **DATE:**____________

Over the last 2 *weeks*, how often have you been bothered by any of the following problems?
(use "✓" to indicate your answer)

	Not at all	Several days	More than half the days	Nearly every day
1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself—or that you are a failure or have let yourself or your family down	0	1	2	3

Topics

- Themes include family, sleep, symptoms, progress, process:

0	time session sorry today great send next now one work thanks see thank please help make able perhaps look
1	feel life think know way things now like want make self feelings people change maybe someone much need others
2	right well great sure appointment feel thank just lol tonight please know get sorry say bye meeting last though
3	eating eat food weight sick drink meal now lunch control great chocolate absolutely day healthy dinner put use really
4	time husband mum family feel children now dad want see said friends also kids home life got school daughter
5	people say angry situation anger situations said way social others like one friends talk someone person behaviour saying know
6	get go know like need things going just think try want one something time good now make day start

Topic vs Schizophrenia

Sleep patterns	day sleep week time bed work mood night get things days	sleep day time feel bed bit things hours morning sleeping night
Family	time husband mum family feel children now dad want see said friends also kids home life	mum money dad brother shopping died enjoy tablets blood bad daughter sister
Food / weight	eating eat food weight sick drink meal now lunch control great chocolate absolutely day healthy	weight stone eat medication gain hospital twelve weigh exercise cut gym
Negative feelings	feel life think know way things now like want make self feelings	feel medication feeling thoughts time mood low head past illness
Crises	get help gp depression pain know medication health therapy sorry appointment last face moment	remember doctor hospital reason police people memory ring shaking headaches door
Social stress	work job time good stress working get school life money wife issues	things back place years thought bit ago home put day coming

Topic vs severity & progress

0	Materials, self-help, procedures	−		10	Unhelpful thinking/habits		
1	Feelings/effects of relationships on sense of self	+	+	11	Work/training/education issues/ goals		
2	Positive reactions/encouragement			12	Agenda/goal setting & review		
3	Issues around food			13	Panic attack description/explanation	−	−
4	Family/relationships & issues with (mostly negative)	+		14	Other healthcare professionals, crises, risk, interventions	++	
5	Responses to social situations			15	Sleep/daily routine	+	
6	Breaking things down into steps	+		16	Positive progress, improvements	−−	−
7	Worries/fears/anxieties	−		17	Feelings, specific occasions/thoughts		
8	Managing negative thoughts/ mindfulness			18	Explaining/framing in terms of CBT model		+
9	Fears, checking, rituals, phobias	−	−	19	Techniques for taking control	−	−

Sentiment/Emotion Detection

- Detect positive & negative sentiment
  - see e.g. (DeVault et al, 2013)
- Detect anger
  - challenge & emotion elicitation in CBT process
- Compared existing tools
  - Manually annotated 85 utterances in 1 session
    - *positive / negative / neutral* (inter-annotator agreement $\kappa = 0.66$)
- Dictionary-based LIWC
  - sentiment 34-45%; anger recall = 0
- Data-based (RNNs) Stanford, trained on news text
  - sentiment 51-54% (no anger)
- Data-based (SVMs), trained on Twitter text
  - sentiment 63-80%

Sentiment/Emotion vs PHQ

	Severity (PHQ)	Progress (ΔPHQ)
Sentiment mean	––	–
Sentiment std dev		+
Anger mean/max	+	
Anger std dev	+	

- More positive sentiment ➔ better PHQ, progress
- More variable sentiment ➔ worse progress
- More/more variable anger ➔ worse PHQ

Predicting final outcomes

- Changes in levels help predicting final in/out-of-caseness:
  - using features from initial and/or final sessions:

	Final In-caseness
Baseline proportion	*26.8%*
First + last session features, incl deltas	**0.71 (0.48)**
Including early PHQ scores	**0.76 (0.51)**

- Features chosen are informative:
  - Levels of sentiment & anger, progress & crisis/risk topics
    - Deltas between sessions
  - PHQ scores at assessment and initial treatment sessions

Predicting dropout

- Can we predict dropout & non-engagement?
  - 148 of 500 did not enter or stay in treatment

	Dropout
Baseline proportion	*29.6%*
Assessment session features	0.65 (0.26)
Treatment session features	**0.70 (0.59)**
Both sessions	**0.73 (0.64)**

- >70% accuracy using initial session features
  - But only by including fine-grained word features

Predicting therapy quality

- Can we distinguish "good" from "bad" therapists?
  - Top 25% vs bottom 25% based on number of patients recovered

	Dropout
Baseline proportion	*50%*
Only high-level features	0.67 (0.63)
Incuding lexical features	**0.78 (0.74)**

- Good accuracy using initial & final session features
  - But mostly by including fine-grained word features

Depression: Summary

- Topic modelling provides useful features:
  - topics correlate well with human-annotated topics and previous study
  - topics correlate with symptom severity and progress
- Emotion detection provides useful features:
  - levels and variability predict symptoms and progress
  - needs care choosing & training tools
- Predicting useful outcome measures:
  - recovery: 71%, 76% with PHQ information
  - dropout: 73%
  - therapist quality: 78%
  - but we don’t entirely understand the last two …

SLADE: Dementia Diagnosis

- U. Exeter dataset
  - 148 diagnosis conversations with doctor (& carer)
    - 70 positive diagnosis of dementia
    - 78 negative diagnosis (Mild Cognitive Impairment in some cases)
  - After referral from GP, memory tests/scans
  - Given diagnosis, advice

- Relatively early stage
  - Can we aid diagnosis?

Dementia & Language

- Vocabulary reduction (e.g. Hirst & Feng, 2012)
  – Authors over long timescales
- Content reduction (e.g. Orimaye et al 2014)
  – Fewer predicates
  – Fewer utterances, shorter sentences
  – DementiaBank: 74%
- Speech features (Jarrold et al, 2014)
  – Including lexical class features
  – Pronoun vs noun vs verb frequencies
  – Small set, healthy controls: 80-90%

- But we have short timescales, diagnosis-dependent content …
  – Advice on driving, legal requirements, future planning
  – And many other features e.g. length
  – Need content-independent features

Conversation-based studies

- Many CA-like studies
  - Watson et al 1999 … Jones et al 2015
- Indicative dialogue-structural features
  - "Lack of fluency"
    - Self-repair
    - Lack of topic coherence
  - Other-repair
    - Types, appropriateness, answering behaviour, lack of corrections
  - Question-answering
    - Avoidance strategies, contentlessness
  - Pausing behaviour
    - Intra- and inter-utterance
  - Backchannel behaviour
    - More contentless utterances vs lower use of continuants?
  - Laughter

Question-answering

- Watson et al (1999)

Normal 75:	Can you remember the name of where you worked?
SDAT 76:	Yeah
Normal 77:	Mm? (as in 'Tell me').
SDAT 78:	Oh yes.
Normal 79:	Well what was the ...
SDAT 80:	I remember those things love I-I can't remember his name now he was a big bully (laughs).
Normal 81:	But what was the name of the place where you worked?
SDAT 82:	And he used to hurry up the steps like this. You know hurry up the steps.
Normal 83:	Yeah. What was the name of the place where you worked?
SDAT 84:	No, that's one thing I'm sorry I can't remember. It was up near a hotel at Paddington anyway I know that much (laughs).

Repair

- Watson et al (1999)

Normal 17:	Don't you have any kids.
SDAT 18:	Huh?
Normal 19:	Any children?
SDAT 20:	Children, well my my fam-family were a heavy family three three or four.
Normal 21:	Oh, you mean a large family.

Normal 25:	Did you have your own children?
SDAT 26:	Ah no I used to go to school right (unintelligible) in reality about that size.
Normal 27:	What would be that size?
SDAT 28:	Can't go to school in the morning 'cause all depends on where you are.

First try

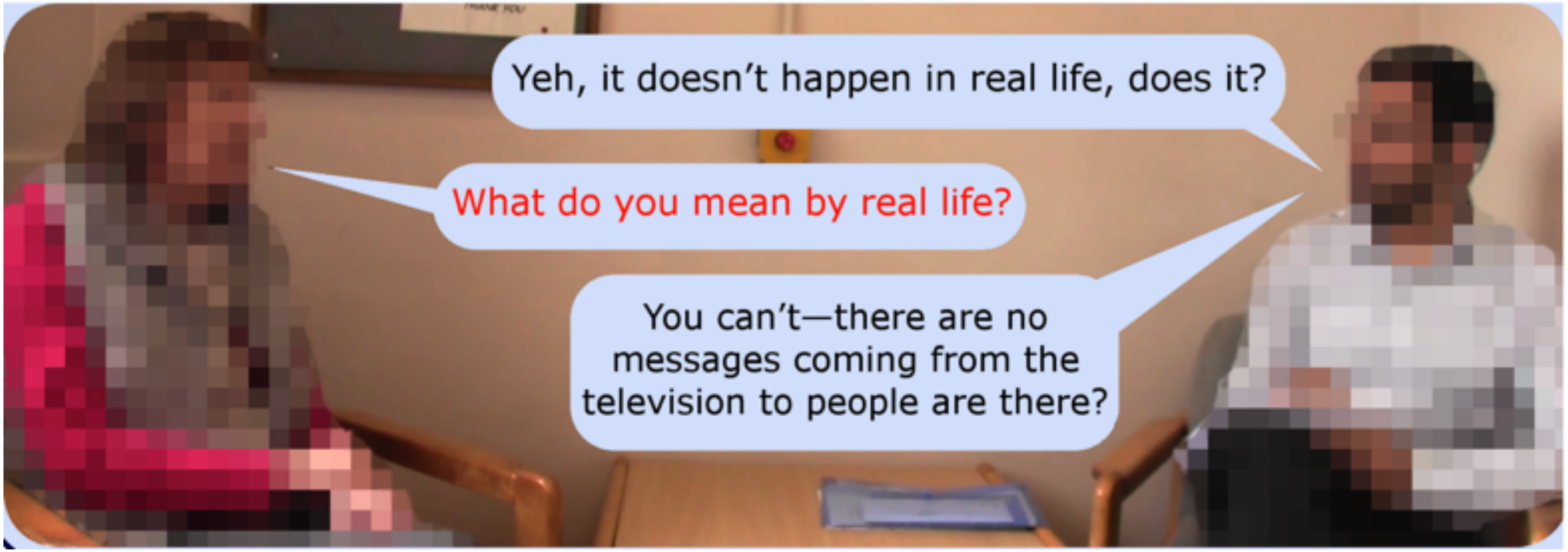
- Simple "content"-independent features:
  - Social indicators:
    - Greetings
    - Contribution of carer
  - Self-repair indices:
    - Pauses, filled pauses, incomplete words
  - Other-repair indices:
    - Repetition, conventional forms
  - Dialogue structure features:
    - Non-answering (short answers, "don't know" keywords, pauses)
    - Carer answering (turn sequences)

- Accuracy c.70% … but:
  - Pauses, "non-answering", edit terms helpful
  - Simple repetition indices not useful (inter/intra-utterance)
  - Simple answering (keywords/speaker changes) only marginal

Next steps

- Self-repair identification via (Hough & Purver, 2014) classifier:
  - In-domain F-score 0.81
  - Transfer to mental health domain: 0.68, per-dialogue correlation 0.95
- Specific dialogue acts for questioning/answering:
  - Questions, answers, backchannels
- Improving other-repair models:
  - Distributional semantics for meaning parallelism
- Big sparseness problem
  - Tagging for repair-related DAs (Surendran & Levow, 2006)
    - `check` 8% turns, 45% f-score, `clarify` 4% turns, 19% f-score
  - Fragment detection in dialogue (Schlangen, 2005)
    - Fragments 5% of turns, 30-40% f-score
- Individual classifiers from Switchboard
  - Questions, backchannels c.80% accuracy

Repair

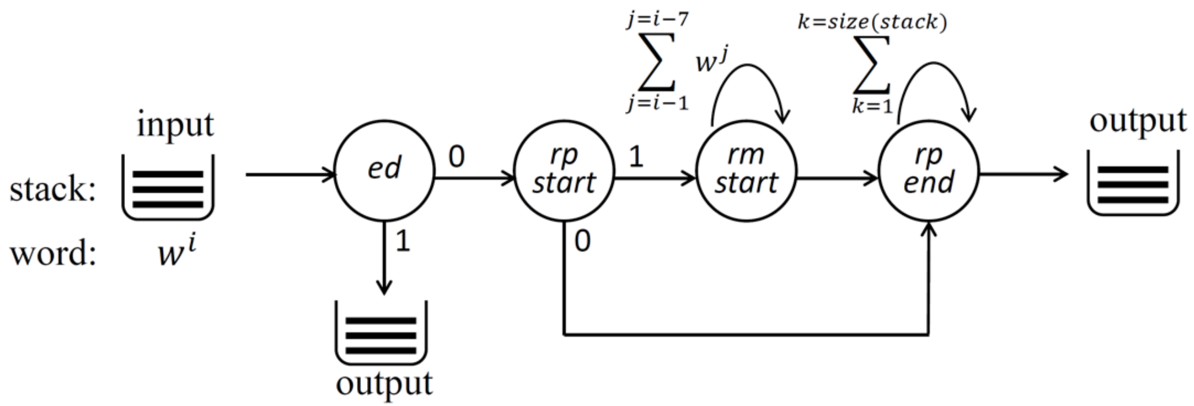


- Schizophrenia data:
  - Significant role of *repair*
  - Patient-initiated other-repair (above)
  - And self-repair:

Did you feel that – *did you despair so much that* – you wondered if you could carry on

Self-repair

- Incremental, information-theoretic repair point classifier



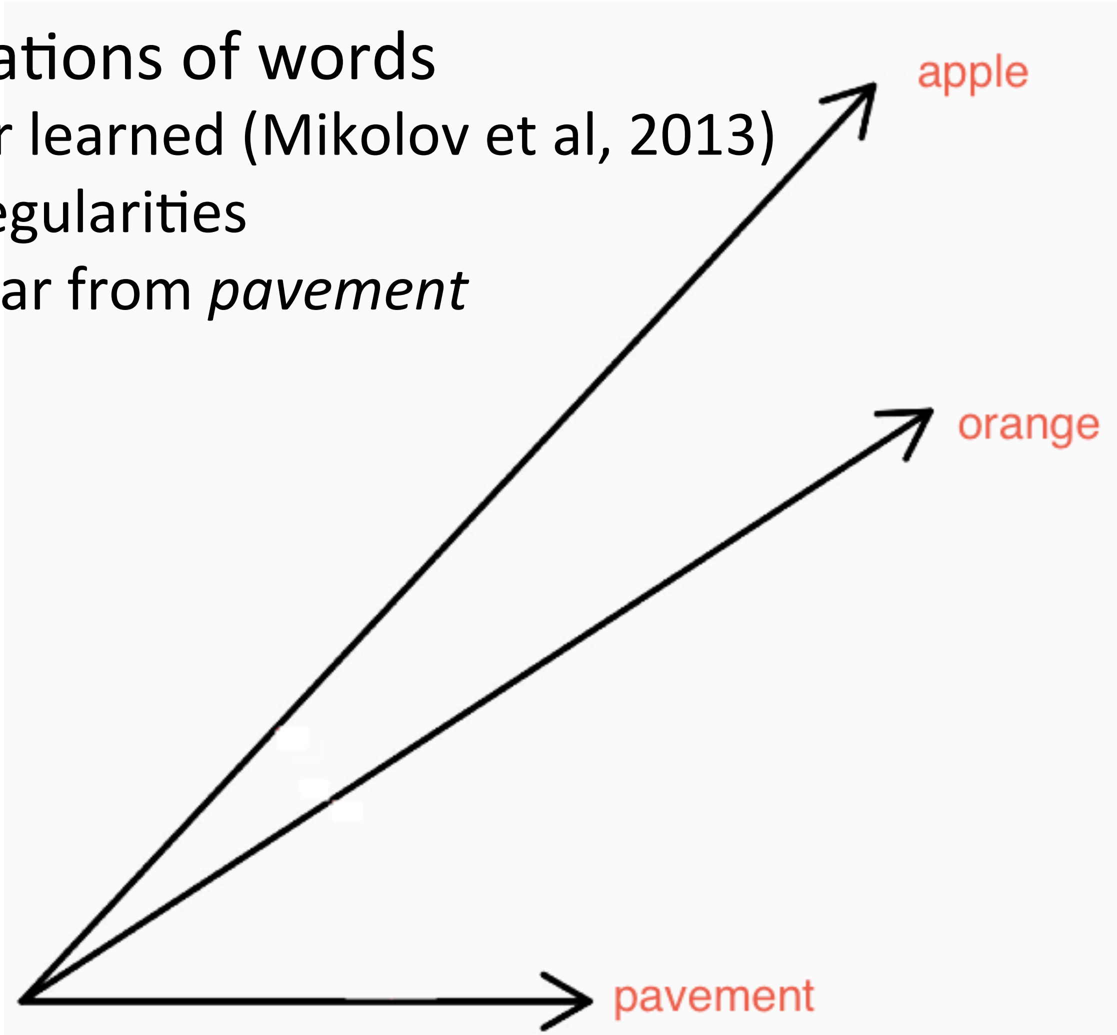
- Domain-general features:
  - Similarities between probability distributions
  - Changes in probability & entropy given repair hypotheses
  - Combined in random forest classifier
  - Near state-of-the-art F-score 0.81, with faster incremental performance
  - Transfer to mental health domain: 0.68, per-dialogue correlation 0.95

Distributional Semantics

- Vector space representations of words
  - Co-occurrence-based or learned (Mikolov et al, 2013)
  - Semantic similarity & regularities
  - *apple* close to *orange*, far from *pavement*
  - *(king – queen)*

    ≈ *(man – woman)*

    ≈ (*uncle – aunt)*



Acknowledgements

The CMSI project was supported by CreativeWorks London, a Knowledge Exchange Hub for the Creative Economy funded by the Arts and Humanities Research Council; and completed in collaboration with Chatterbox Labs Ltd & the Barbican

The PPAT & AOTD projects were supported by Queen Mary University of London's EPSRC-funded Pump-Priming and Innovation Funds, and PsychologyOnline Ltd; and completed in collaboration with PsychologyOnline Ltd and iLexIR Ltd.

The project ConCreTe acknowledges the financial support of the Future and Emerging Technologies (FET) programme within the Seventh Framework Programme for Research of the European Com- mission, under FET grant number 611733§