Miscommunicating with Computers

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with many others

but mostly Julian Hough and Christine Howes

Repair Phenomena

A: It's in the **yell-, sorry, purple** square
B: **The *what* square**?
A: **Purple**.
B: **You mean yellow.**
A: Oh yeah. **Yellow**.

- Self- and other-repair
- Clarification (repair initiation)
- Positions 1, 2, 3, …

Dialogue Systems

- Clarification & confirmation **by systems:**

> U: When's the next bus to Wood Street?
> S: Sorry, I didn't understand that. Please repeat.

> U: When's the next bus to Wood Street?
> S: Going to WOOD STREET. Did I get that right?
> U: Yes.

- ASR inaccuracy
- Domain mismatch
- Generally confidence-based (ASR/domain)

Clarification by Systems

- Designing optimal questions (e.g. Stoyanchev et al 2014):

U: Do you have anything other than the [???] plans
S: Which plans? / Anything other than what?

- Learning to adjust strategy/confidence (e.g. Bohus & Rudnicky 2005)
- Integration with general decision process and domain learning (e.g. PARLANCE project)
- But these don't give us methods for ***detecting*** repair

Clarification by Users

TTS: I calculated a route to Brian's house. It is 4.13 miles long and should take around 9.0 minutes .

SR: what is my next turn

TTS: Go East on Miranda Ave

SR: what is the next turn

TTS: Make sharp right on Arastradero Rd

SR: what road

TTS: I'm sorry, I do not understand what you mean by: what road

TTS: Please try rephrasing that.

SR: what road do i turn on

TTS: I'm sorry, I do not understand what you mean by: what road do i turn on

TTS: Please try rephrasing that.

SR: what road do i turn on and where is alma street from there

TTS: Did you want to plan a route from there?

SR: what was the last instruction you gave me

TTS: Sorry, there is no instruction to repeat

SR: what was the last route instruction you gave me

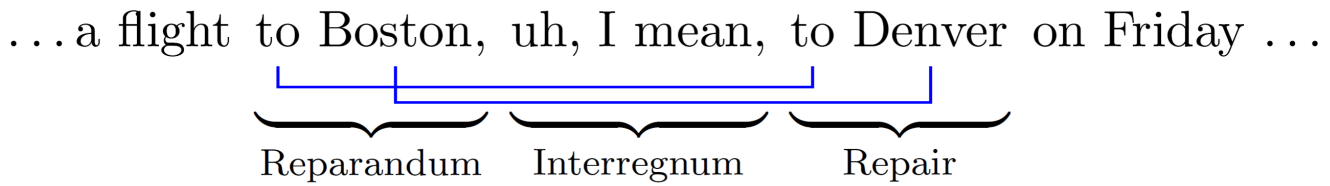
TTS: Sorry , there is no instruction to repeat

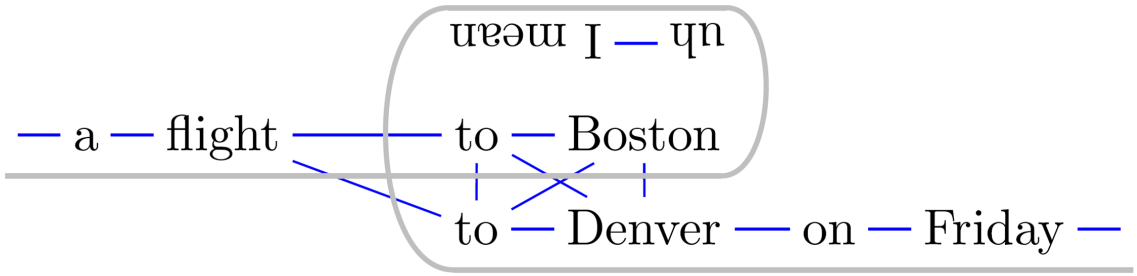
SR: i want to go to brian's

TTS: Ok , I will plan a route to Brian . Would you like anything else?

Self-Repair

- Disfluency detection for ASR
  - Identify reparandum extent and remove
  - e.g. transduction: Johnson & Charniak, 2004

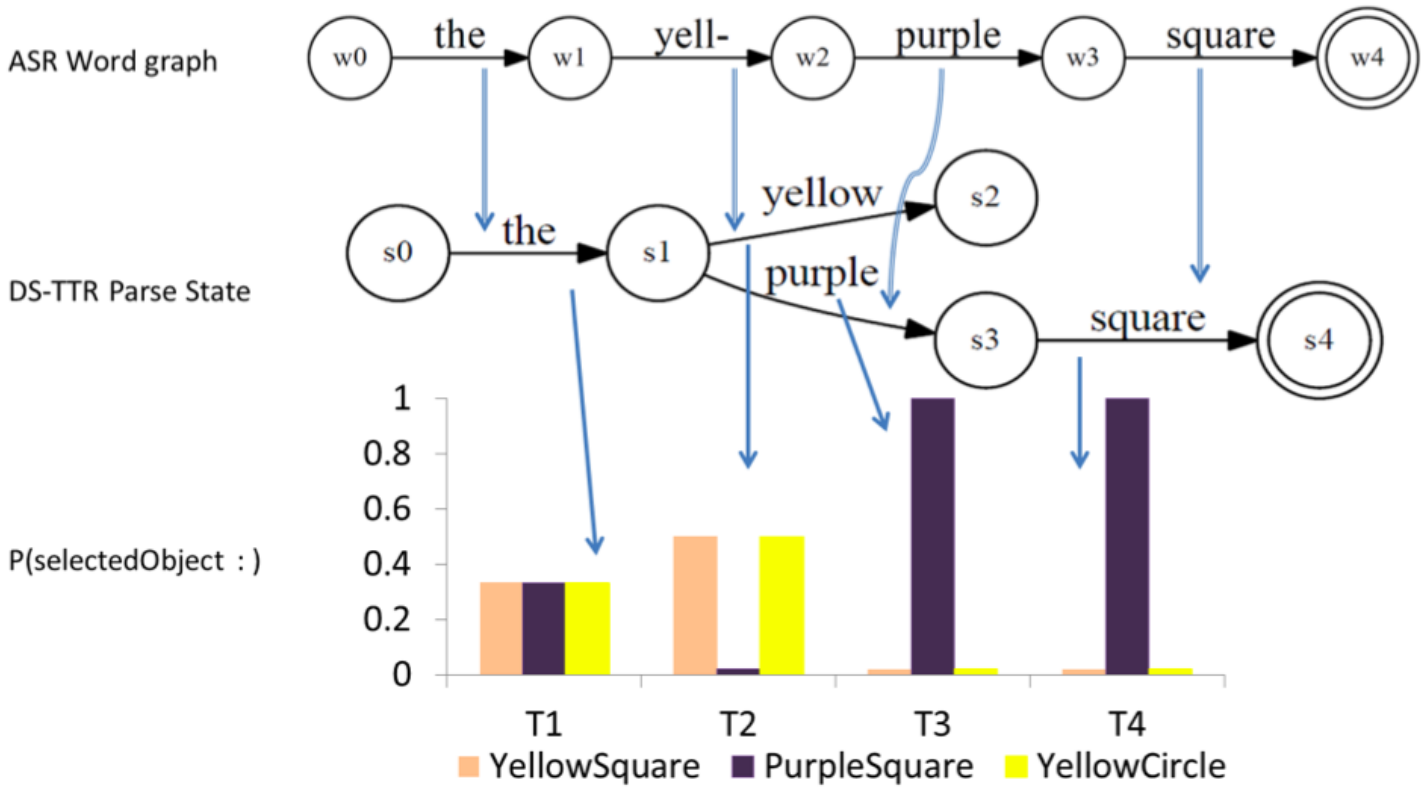




- But this is stuff we need! E.g. for anaphoric reference:
  - "The interview was …. it was alright" (Clark, 1996)

Self-Repair is incremental

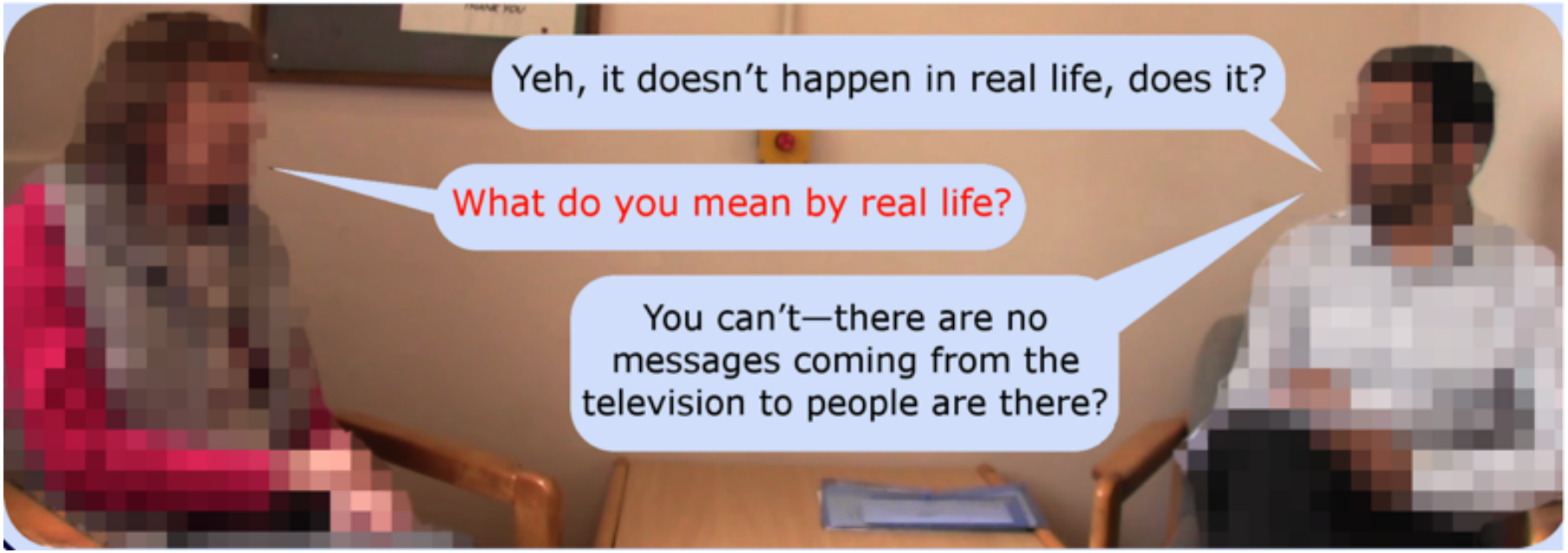
- Effect on incremental processing (Brennan & Schober, 2001)
  - See DYLAN system (Hough & Purver, 2014)



Self-Repair models

- We'd like a model which is:
  - Incremental
  - Able to track context contributions
- Existing models either:
  - Lose the reparandum and/or repair
    - (e.g. Johnson & Charniak, 2004)
  - Need the whole sequence
    - (e.g. Georgila, 2009)
  - Work incrementally but maintain all hypotheses
    - (e.g. Heeman & Allen, 1999; Zwarts et al, 2010)

Human-Human Repair



- Language processing for psychiatric therapy:
  - Diagnosing symptoms
  - Predicting outcomes

Doctor-patient communication

- Schizophrenia therapy (face-to-face)
  - Symptoms and severity:
    - Positive symptoms: delusions, hallucinations, beliefs
    - Negative symptoms: withdrawal, blunted affect, alogia
  - Non-adherence to treatment:
    - About half of patients non-adherent in the year after discharge from hospital (Weiden & Olfson, 1995)
    - Risk of relapse 3.7 times higher (Fenton et al, 1997)
- Depression & anxiety therapy (online)
  - Symptoms and severity
  - Progress and dropout rates
- Can features of dialogue help understand/predict?
  - Topic structure: focus on symptoms, treatment
  - Repair structure: coordination, shared understanding

Prediction Results

- Predicting symptom severity reasonable:
  - Depression (PHQ) 70%
  - Schizophrenia (PANSS) 62%
  - (with topic/sentiment features)
- Predicting non-adherence (patient turns only):

Features	Weighted F (%)
Baseline: class of interest	**44.8**
Human: text only	**68.6**
Human: text + video	**78.0**
Lexical features	**70.3**
Topic features	**66.2**
Automatic topics	**54.1**

- So how can we improve this? Repair …

Repair in Therapy Dialogue

- Self-repair (e.g. P1SISR, P3SISR)
- Articulation, formulation

Dr: You probably have seen so many psychiatrists **o o over the years**

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

P: Where I go to do **some printing** **lino printing**

Dr: **Clorazil** or
P: Yeah
Dr: **Clozapine** yes

Repair in Therapy Dialogue

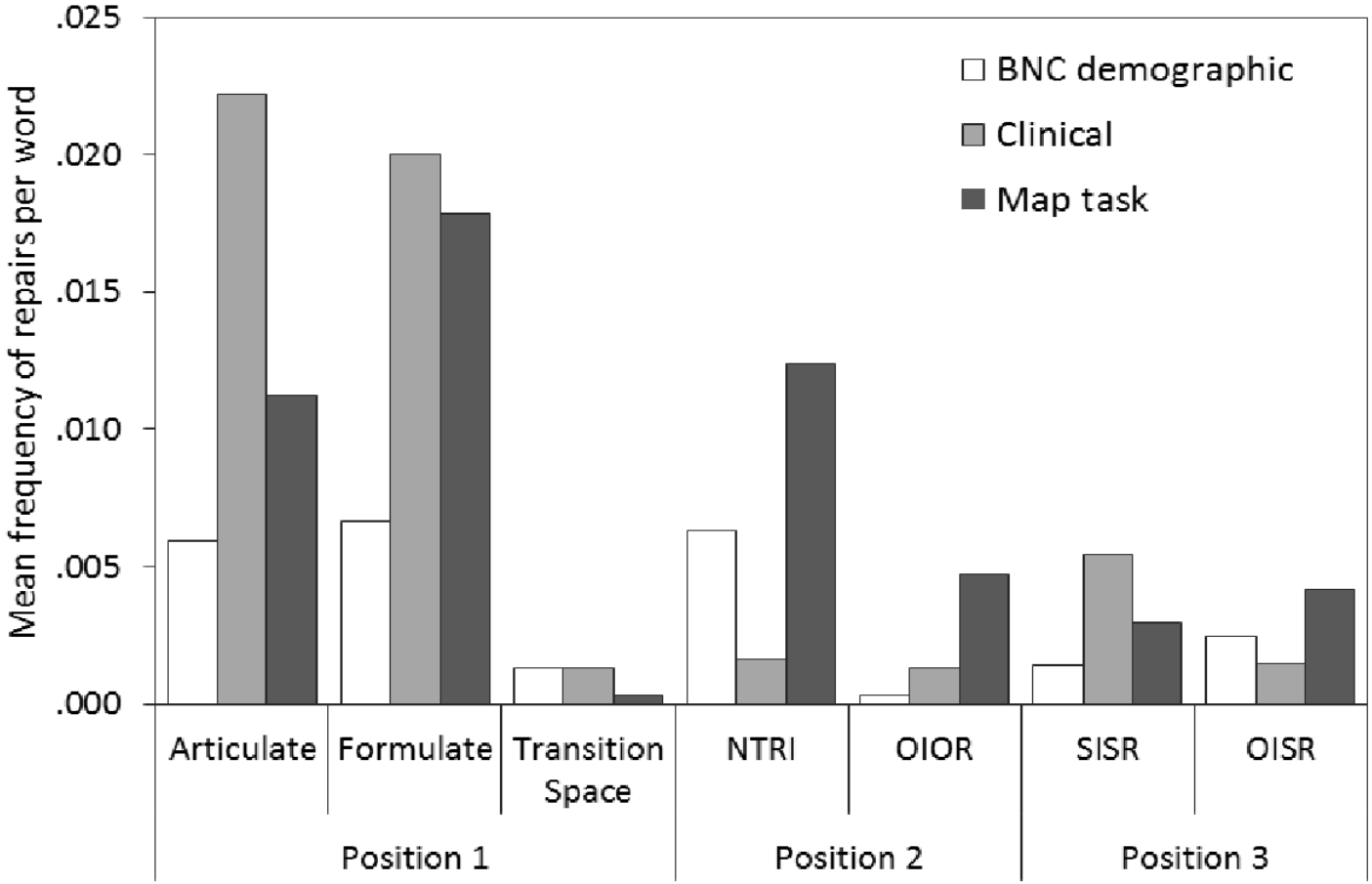
- Other-repair (e.g. P2OIOR)

Dr: Rather than **the diazepam** which I don't think is going to do you any good
P: **the valium**

- Repair initiation (e.g. P2NTRI then P3OISR)

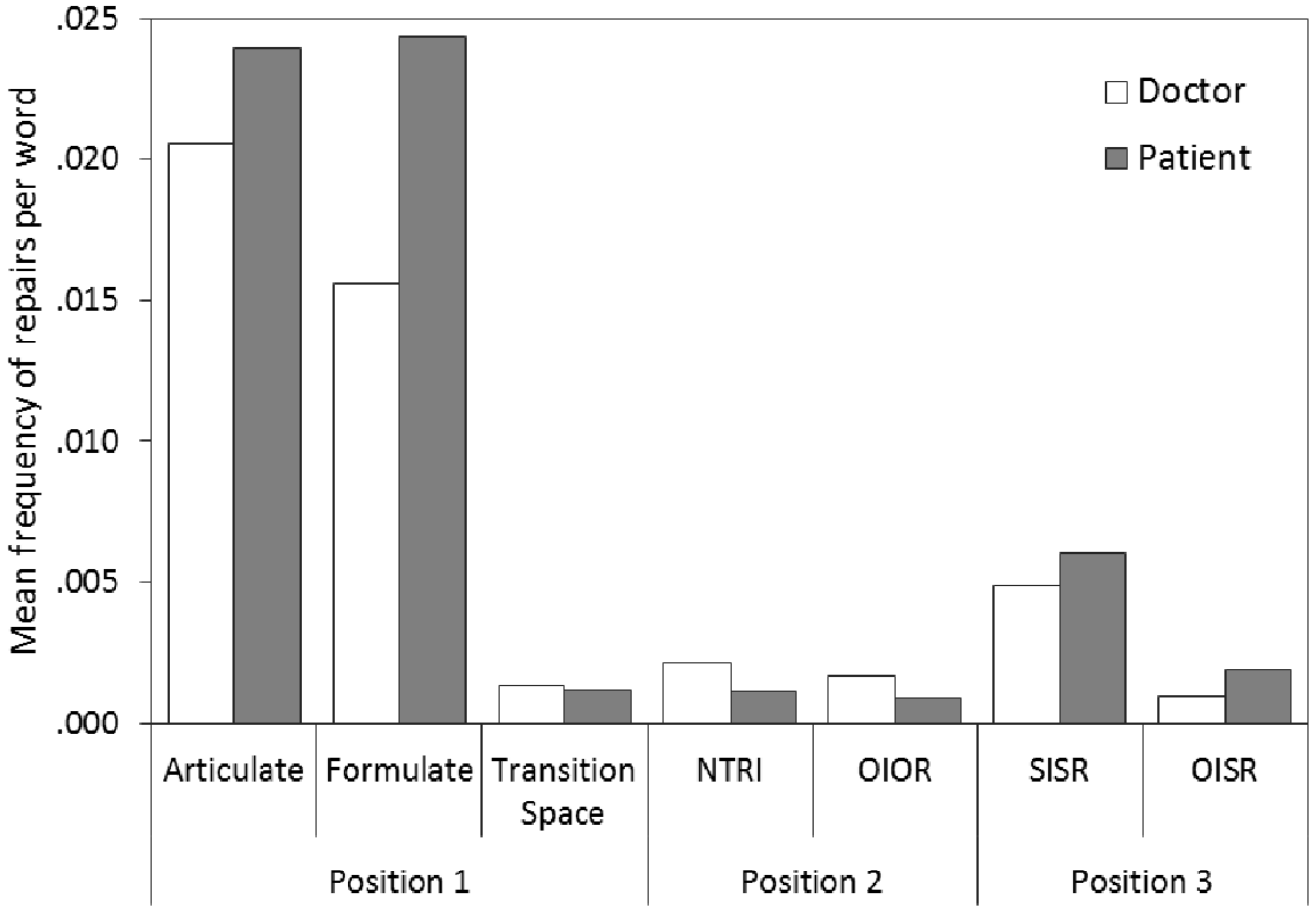
Dr: Yeh, it doesn't happen in real life does it?
P: **What do you mean by real life?**
Dr: **You can't - there are no messages coming from the television to people are there?**

Comparison with other contexts



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

Patient-doctor comparison



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

Detecting Other-Repair

- Need to detect instances of repair
  - Next-turn repair initiation and P2 repair
- How do we approach this?

- Define some features that characterise repair
  - (which we can extract automatically)
- Learn a statistical model
  - (using some standard machine learning algorithm)

Features

- Sometimes we see specific lexical / phrasal items:

Dr: Ok you have done it before
P: **Pardon?**
Dr: If you have done it before

Dr: Who is your GP now
P: **What?**
Dr: Who is your GP

P: They're not negative erm but they're positive as i eh erm it's like imagining how your life will be
Dr: Ok, ok, ok so thinking about how
P: **Do you know what I'm talking about?**

Features

- Sometimes we see repetition/parallelism:

Dr: Yep well that is a possible side effect
P: **Side effect?**
Dr: Of the err Haliperidol

Dr: One thing that I ask you is when you were low in mood did you have suicidal thoughts
P: **Did I have ...?**
Dr: Suicidal thoughts

Features

- Sometimes it's more complex than that

Wiz: go straight for four blocks turn left at wall street
Subj: **turn left where**
Wiz: turn left at wall street

TTS: Make sharp right on Arastradero Rd
SR: **what road**

Wiz: after left at elm street turn right at lois lane
Subj: **was that right on lois lane or left on lois lane**
Wiz: turn right at lois lane

Features

- Sometimes it's more complex than that:

Dr: Are you suspicious are you suspicious of people
P: **Suspicious**?
Dr: Paranoid
P: **Jealous**?
Dr: Jealous yeah

Dr: Paroxitine
P: **Fluoxitine**
Dr: Ah Fluoxitine

Features

- Sometimes it's more complex than that

Dr: Who's your key worker there do you know
P: **Err the person who comes to see me?**
Dr: Yeah the person you see most often

Dr: Do you do you really feel it or is it a sensation
P: **Is it what I'm thinking is that what you mean?**
Dr: No is it just err the mind playing tricks on you

Dr: was it couple of months three months
P: **Since I saw you**?

Dr: Aaa so have you had any more thoughts about studying
P: **What music?**

Features

- Sometimes it's more complex than that

Wiz: go straight for three blocks turn right at wall street
Subj: **please repeat left where**
Wiz: go straight for three blocks turn right at wall street
Subj: **left where**

Subj: how long
Wiz: dave's house is sixteen minutes away
Subj: **was that one six or six zero minutes**
Wiz: six minutes away

Requirements

- They're context-dependent
- They need semantics
- They need phonology
- They even need spelling

- They're incremental
- They can be very sparse

Detecting Other-Repair

- Define features manually, extract automatically
- Linguistically/observationally informed:
  - Wh-question words, closed class repair words
  - Repetition, parallelism with prior turn(s)
  - Backchannel behaviour, fillers
  - Pauses, overlaps
- Brute force:
  - All the unigrams used (patient-only to avoid doctor specificity)

- Train SVMs to detect NTRIs & P2Rs
  - 44,000 turns of which 567 NTRIs (159 patient), 830 P2Rs (262)
  - 5-fold cross-validation
  - (Howes et al, 2012-14)

Results – balanced data

- Balanced data (i.e. **small** dataset), patient only:

Target	Features	Accuracy (%)
NTRI	Repeated proportion	61.2
NTRI	All high-level	83.2
NTRI	All unigrams	82.4
NTRI	All features	86.3
P2R	Repeated proportion	61.5
P2R	All high-level	78.5
P2R	All unigrams	77.1
P2R	All features	79.8

- But of course the real data's not balanced …

Results – repair detection

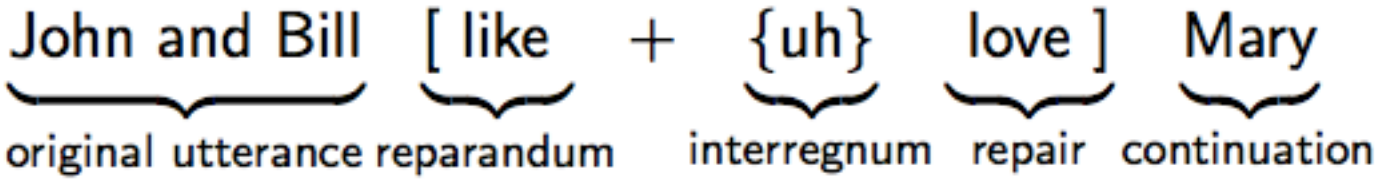
- On balanced data: accuracy 80-86%
- Full dataset, patient only:

Target	Features	P (%)	R (%)	F (%)
NTRI	OCRProportion	85.7	22.6	**35.8**
NTRI	All high-level	42.8	40.6	**41.4**
NTRI	All features	44.9	43.6	**44.0**
P2R	OCRProportion	56.4	11.8	**19.6**
P2R	All high-level	36.2	28.4	**31.6**
P2R	All features	43.8	30.3	**35.4**

- We'd like to do better!
  - Audio/video: intonation, non-verbal behaviour
  - Context: follow-up dialogue turns incl. other-person reaction
  - Semantic and pragmatic parallelism

Detecting Self-repair

- No grammar; no similar data …
- Probabilistic / information-theoretic model
  - (Hough, to appear)



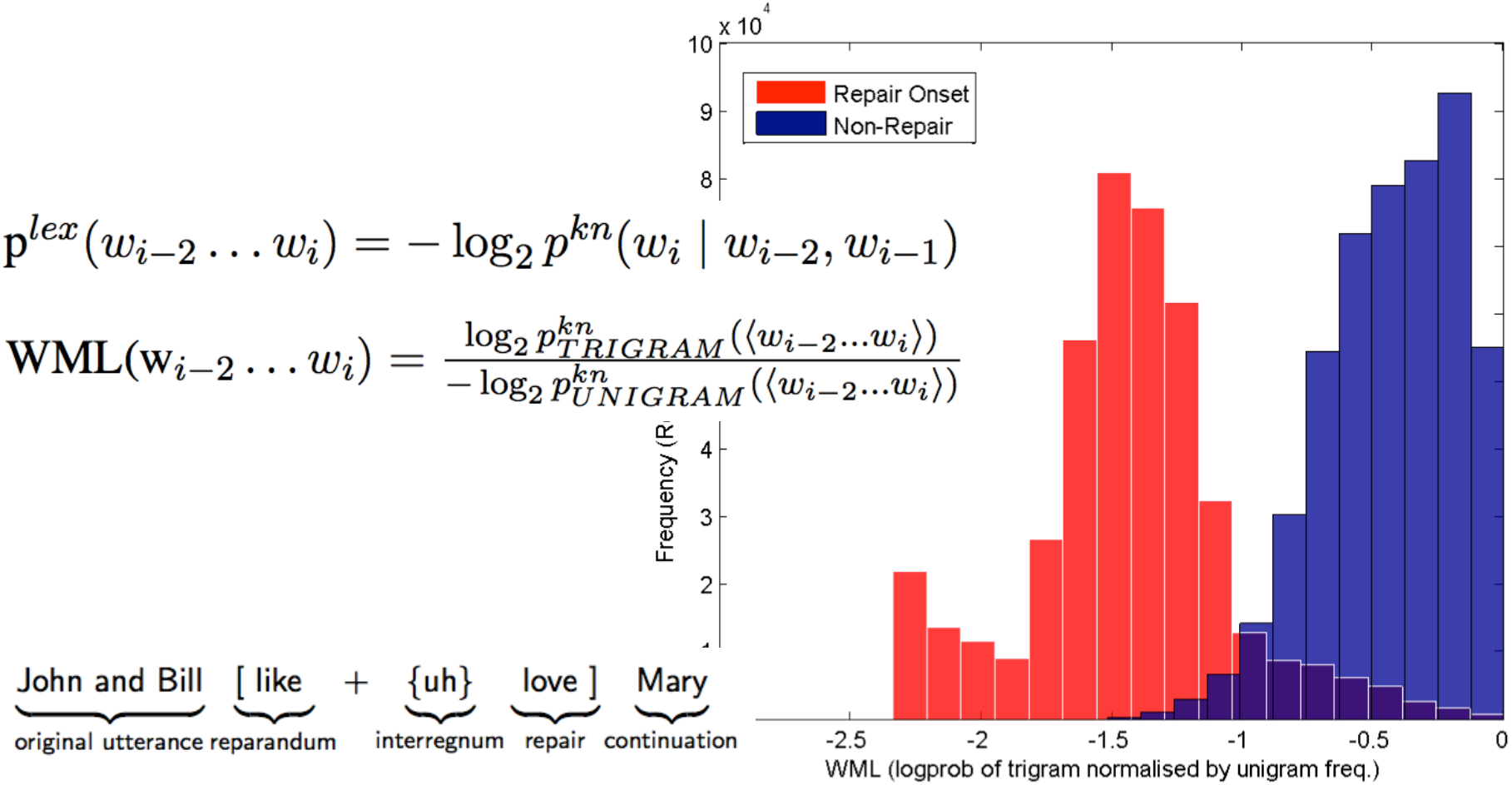
- Interregnum: characteristic words, fillers
- Repair & reparandum boundaries: changes and/or (dis)similarities in *probability* and *expectation* (lexical, syntactic, semantic)
- Incremental process:

  1: repair onset 2: reparandum start 3: repair end

Lexico-syntactic distribution

$$\mathrm{p}^{lex}(w_{i-2} \ldots w_i) = -\log_2 p^{kn}(w_i \mid w_{i-2}, w_{i-1})$$

$$\mathrm{WML}(\mathrm{w}_{i-2} \ldots w_i) = \frac{\log_2 p^{kn}_{TRIGRAM}(\langle w_{i-2} \ldots w_i \rangle)}{-\log_2 p^{kn}_{UNIGRAM}(\langle w_{i-2} \ldots w_i \rangle)}$$



Self-repair: Results

- Accuracy on Switchboard corpus (held-out):

detection	precision	recall	F-score
w_{rp}^{start} position	0.862	0.755	0.805
repairs in turn	0.904	0.787	0.841

- Good, and incremental!
  - Comparable to (Zwarts et al, 2010) … but 1 word, not 4.6
- Accuracy on therapy corpus:

detection	precision	recall	F-score
w_{rp}^{start} position	0.527	0.536	0.532
repairs in turn	0.682	0.679	0.680

- Good for coarse-grained measures (correlation 0.9)
- But not yet good in detail

What have we learnt?

- We need computational models of repair
  - But different from standard ones
- We can do a reasonable job
  - On self- and other-repair
  - Using fairly low-level features
- Doing better is a difficult task:
  - Semantics, pragmatics, phonology, intention … ?