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7th INTERNATIONAL CONFERENCE ON MEANING AND
KNOWLEDGE REPRESENTATION (4, 5 and 6 July, 2018)

Session 5 – 5th July 2018

Motivating a linguistically orientated model for a conversational software agent

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Overview

- Context – Conversational based technology
- Issues – Turing Test? Chatbot vs CSA qualities
- Why RRG?/Approach/Stages
- About RRG/Goals of Linguistic theory
- Requirements for the CSA
- Motivating elements
 - Speech Act Theory , Speech Act Constructions (SAC), Derived parser
 - Intentions, BDI model and planning model
 - Knowledge Model
 - Dialogue Model
- Motivating Questions
- Conceptual framework – 3 Phases/Design Framework
- Implementation (prototype) and findings
- Contributions, significance, originality and conclusions

1. Conversation Based technology

The need for intelligence

“By 2020, 30% of our interactions with technology will be through “conversations” with smart machines” (Gartner, 2015)

Figure 1: Good, bad and ugly of conversation devices

Focus > Conversational Software Agents (CSA)

WhosOn

'Bots: the good, the bad and the ugly

Testing, testing!

Developed by Alan Turing in 1950, the Turing Test is an indication of the intelligence of a computer. The test requires that a human being should be unable to distinguish the machine from another human being by using the replies to questions put to both.

The chatbot predecessors

1966: Eliza

Created as a tongue-in-cheek simulation of a therapist, Eliza could only mimic human conversation by matching user prompts to scripted responses. While she didn't pass the Turing Test, she's widely recognized as the first of the chatbots.

1972: Parry

Described as Eliza with attitude, Parry was designed to simulate a person with paranoid schizophrenia. In fact, Parry and Eliza met several times. Despite their similarities, Parry was certainly more advanced than Eliza.

1988: Jabberwocky

As one of the earliest attempts of creating artificial intelligence through human interaction, Jabberwocky was primarily used as a source of entertainment.

1996: Clippy

Most of us will remember this little guy. Clippy the paperclip was available to offer you a piece of smart advice whenever you opened a Microsoft Office program. Thanks, Clippy, but we already knew where the recycle bin was and, unfortunately, that's where Microsoft sent him in 2007. Rest in peace buddy.

1996: IBM's Watson

Watson uses natural language processing and machine learning to pull intelligent insights from data. As one of the only AI technologies to gain wide commercial pick up, Watson has recently claimed to be better than human doctors when diagnosing cancer.

2001: Smarterchild

The best friend of choice for any lonely 90s kid with a depressingly dry MSN messenger contact list, Smarterchild may have been a novelty, but it's widely considered as a significant precursor to Apple's Siri and Samsung's S Voice.

2006: Siri

While Siri isn't truly a chatbot, it is the earliest bot that comes to mind when most people think of the technology. That being said, most of us don't actually use it.

2015: Cortana and Alexa

Microsoft's Cortana and Amazon's Alexa were the technology giants' answer to the intelligent personal assistant. Using natural language processing, both assistants can receive, recognize and respond to voice commands.

2016: Tay

Unsuccessfully designed to imitate the social habits of a typical teenager, Microsoft's social experiment Tay quickly developed intelligence to rival that of a sex-crazed neo-Nazi. Seriously, just Google it. Unsurprisingly, Tay disappeared from social media after a few hours and we haven't heard from it since.

2016: Facebook Messenger Bots

Allowing developers to design and develop bots for Facebook users to interact with, Facebook's messenger bot army quickly increased to 11,000 bots. Naturally, not all of them are fantastic, but as users become used to bot technology, we're likely to see more emerging from tech giants.

The new generation

A step too far?

Entertainment, not intelligence

1990: Alice

Alice, the natural language processing chatbot, was inspired by Eliza. As one of the strongest programs of its type, Alice won the Loebner Prize — however, it still failed to pass the Turing test.

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2. Turing Test – is it relevant?

- Aspirational benchmark
- Human discourse
- AI-Hard problem
- Positive – Customer outcomes and experience
- Negative – Chatbot bubble (Wallace 2018) – Loebner prize
- Search for: if it behaves intelligently, it is **intelligent**.

3. Chatbots vs CSA

The **need for more intelligence**

Chatbots – single turn

Conversational Software Agent Qualities

- Human-machine interface (text)
- Understands context
- Applies logic
- Use natural language understanding and processing
- Understands what is said (intent)
- Explainable
- Story comprehension
- Formulate a response
- Learns and adapts

4. Why RRG? / Approach / Stages

Challenges of NLU and meaning

- Periñán–Pascual (2013): eligibility
- (1) Morphosyntactic structures (2) grammatical rules (3); monostratal theory (4); Own typological adequacy

Approach – unique framework, model/theory interaction, communicative

- Language levels, interface between syntax, semantic, and pragmatics
- Language Model: **RRG and the clause**

Stages

- Simple sentences → Linguistic act (**Speech Act**) – SA
- Understand the utterance
- Agent attributes
- (Utterance) **Message** from USER → AGENT
- Agent's belief – Knowledge representation (KR)
- Plan-based dialogue (response) **Message** AGENT → USER

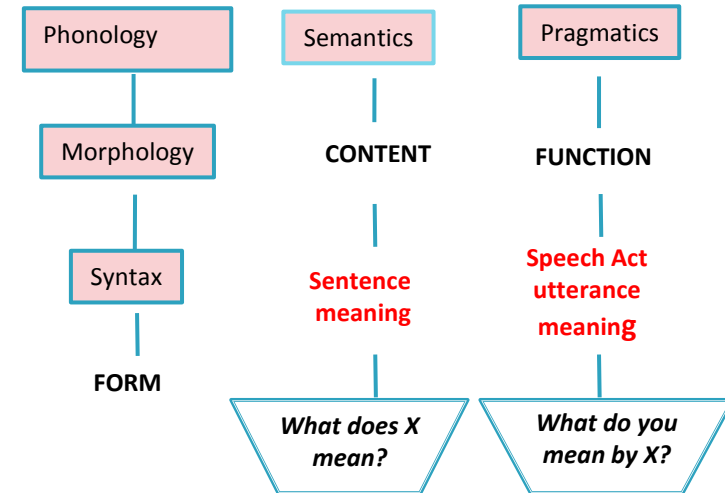


Figure 1: Language interfaces

5. About RRG :LSC and LS

- RRG is a **functional** model.
- It views language as a communicative social action.
- Layered structure of the clause (**LSC**) = **PREDICATE + ARGUMENT + NON-ARGUMENTS**.
- Logical Structure (LS) – **semantic meaning of the sentence**.
- **Lexicon** - mental dictionary - lexical entries contain semantic features and constraints.
- It maps the **syntax(structure): LSC** ⇔ **semantic (meaning): LS** the actual form of the sentence using two different **LINKING ALGORITHMS**.
- RRG parser (algorithm) checks the grammar (rules) of English. **Specialised parser (CSA)**
- RRG facilitates syntactic, semantic and information structure (**FOCUS & TOPIC**)

Gareth ate everything fast

(BNC ADY 1079) (Butler et al, 2009) → Figure 5
SYNTACTIC:

SENTENCE (CLAUSE (<CORE> <NP> gareth (<NUC> (<PRED> <V> ate)) (<NP> (everything))) (PERIPHERY fast))

SEMANTIC:

[<IF> ASS <TNS> PST, do'(ACT:Gareth, (eat'(Gareth <NOM>, pizza <ACC>)))] & INGR consumed' (UND:pizza)]

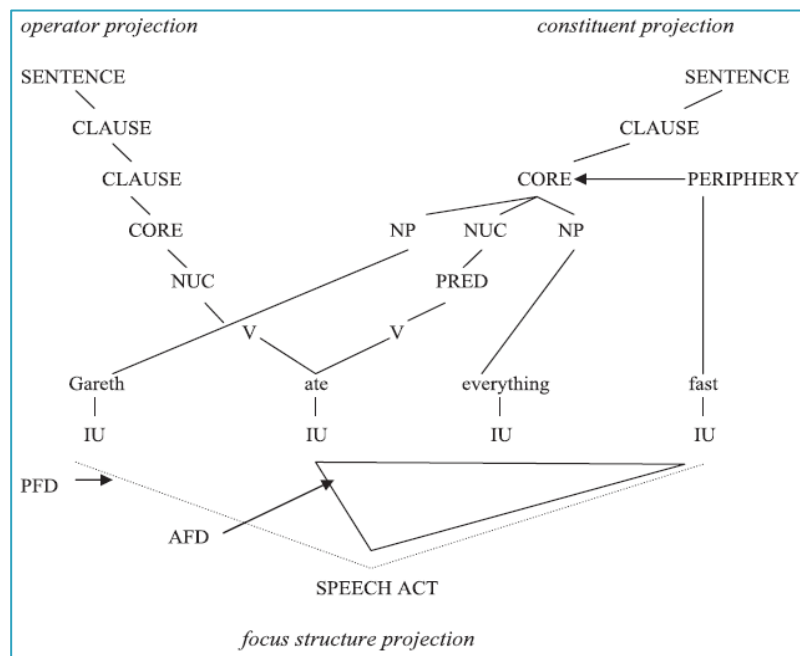


Figure 2 - An English sentence with three representations

6 Motivating – Goals of Linguistic Theory

Van Valin and LaPolla (1997) defines goals:

- 1) Description of the language phenomena
- 2) Explaining the linguistic phenomena
- 3) Understanding the cognitive basis of language
 - Processing
 - Knowledge
4. Computational adequacy

RRG Linking Algorithm (see paper)

7. Requirements for the CSA

AGENT + INTELLIGENT DIMENSION (S) = INTELLIGENT AGENT

INTELLIGENT TAXONOMY Behavioural, Social, Ambient, Collective, Genetic, and **COGNITION**

COGNITION = BDI + Rational Interaction

CA = Interpretation + Dialogue Mgt + Response Generator

CSA = CA + RRG + SA + COGNITIVE + KB (Panesar, 2017)

8. Motivating – Speech Act Theory

- **Speech** (linguistic) **Act** (SA) Theory (Searle, 1969)
- He states ‘speaking a language is engaging in rule governed form of behaviour’ and that ‘illocutions are intentional acts;

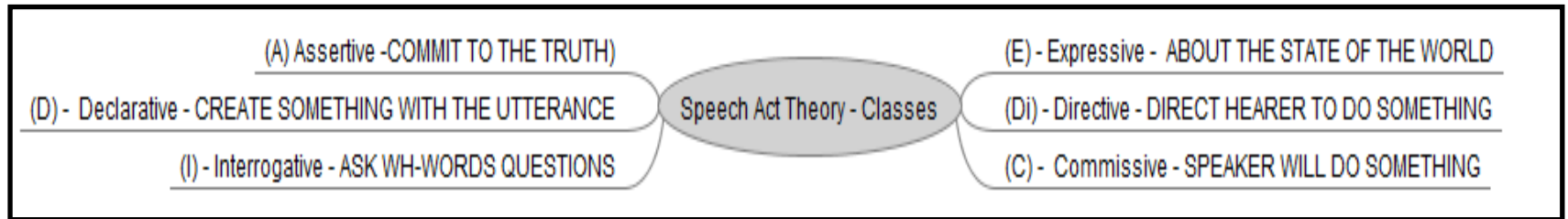
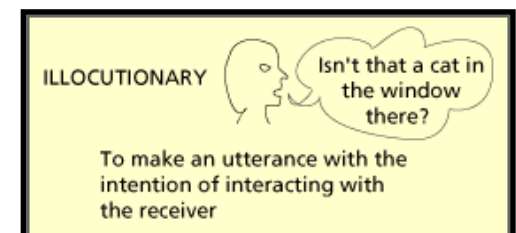


Figure 3 – Speech Act message types

- 3 actions associated with an utterance include:
 1. Locution:
 2. **Illocution: illocutionary act (speaker's intention) [SI]** for A, Di and I message types
 3. Perlocution:
- Intentionality – leading to an action
- RRG – illocutionary force (IF) links to the type of speech act

Figure 4– Illocutionary act (n,a, n.d)



9. Motivating – Derived RRG Parser with SACs

- Nolan (2014) considers constructions as structural grammatical objects > Extension of Constructions schemas (CS)
- No use of syntactic inventory/syntactic templates
- RRG input -> speech act constructions (SACs)
- Updateable via the RRG Linking algorithm and Lexicon – richer

LEXICAL ENTRY	POS-TYPE	VERB TENSE/ ASPECT	DEF	P TYPE	NO	GR	CASE	ANIM	HUM	LOGICAL STRUCTURE (LS)
ate	VERB	PST	DEF+/-	3	SG	M/F	DNA	ANIM	HUM	<tns:pst <do'(x, [eat'(x, y)]) & BECOME consumed'(y) >>
eat	VERB	PRS/ FUT	DEF+/-	3	SG	M/F	DNA	ANIM	HUM	<tns:prs <do'(x, [eat'(x,y)]) & BECOME consumed'(y) >> <tns:fut <do'(x, [eat'(x,y)]) & BECOME consumed'(y) >>
eating	VN	PROG	DEF+/-	3	SG	M/F	DNA	ANIM	HUM	<tns:prs <asp:prog <do'(x, [eat'(x, y)]) & BECOME consumed'(y) >>>
is	VBE	DNA	DEF+	DNA	DNA	DNA	DNA	DNA	DNA	be'(x,[pred'])
hungry	ADJ	DNA	DNA	DNA	DNA	M/F	DNA	ANIM	HUM	DNA
restaurant	N	DNA	DEF+/-	DNA	SG/PL	DNA	DNA	DNA	DNA	DNA

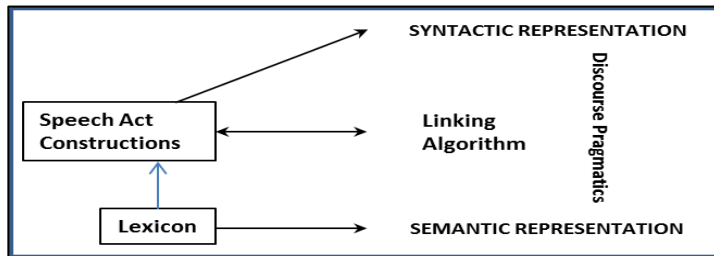


Table 1 – Snapshot of the Lexicon (Panesar, 2017)

Figure 5– Parser for the CSA

Figure 6 – Empty SAC (Speech Act Construction) (Panesar, 2017)

ASSERTIVE:ATE RRG [NP VERB NP], [PN VERB], [ADV PN VERB DET N], [PN VERB N ADJ], [PRP DET N PN VERB DET N], [PN VBE VERB N], [PN PRP DET N PRP DET N], [PRO VERB DET N], [PN VERB NP], [PN VERB DET N], [NP VERB QNT N], [DET N VERB DET N], [DET N VERB QNT N], [NP VERB (DET) (ADJ) N (ADJ)], [PN VERB DET N ADJ], [PN VERB (DET) ADV N ADJ], [PN VERB DET N PRP DET N], [PN, VERB, N, PRP, DET, N], [PN VERB N PRP DET N] RRG NONE RRG UTTINPUT RRG WSPACE RRG DEFAULT ASSUMPTION (1ST NP = 'ACTOR") RRG NO PARTICULAR SPEC RRG NONE RRG CONTAINS A NOUN PHRASE BEFORE AND AFTER THE VERB RRG DEFAULT RRG TRUE/FALSE RRG ASSERTIVE RRG NARROW FOCUS ON THE ELEMENT RRG LOG STRUCTURE TO ADD

10. Motivating – Intentions, BDI Model & Planning Model

(Panesar, 2017)



Intentional agent

BDI = Belief, Desire, Intention

- Perception
- Searle (1985:p4) – SAs differ due to different **mental states**
- Reason with knowledge that they believe to be **TRUE** or **FALSE**, and to provide a response.
- Operators characterise what agents must **know (KNOWLEDGE MODEL)** to perform actions intended to achieve their goals
- **PLANNING MODEL** – to rationalise a correct plan (to achieve these goals), and pursue the plan based on these intentions (RRG logical structure)

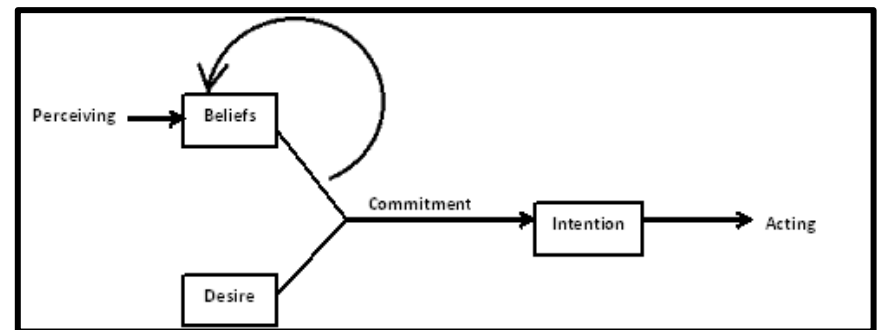


Figure 7– A BDI model of an intelligent agent (Allen, 1995)

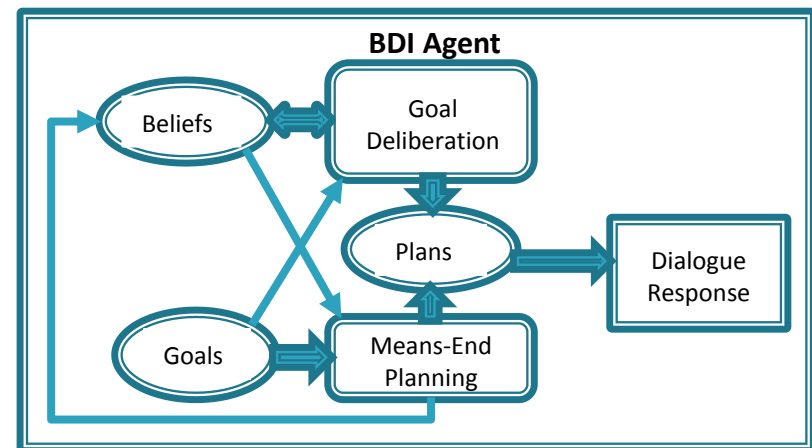


Figure 8– BDI Agent structures, processes and role (adapted from (Pokahr, Braubach, Haubeck & Ladiges, 2014)

Example – ‘Gareth ate the pizza’

BDI states

Belief: **Gareth**;

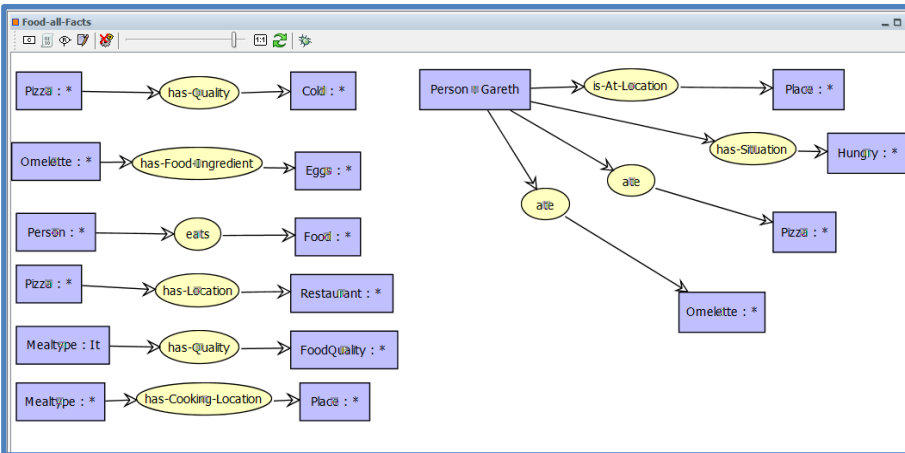
Desire – ‘**eat**’;

Intention: **consume pizza**;

11. Motivating – Knowledge Model



SHARED and **INDIVIDUAL BELIEFS** cognitively → mental knowledge.



- Conceptual graphs (CGs) (Sowa, 1986), Vocabulary, **First order logic (FOL)** created in COGUI as in Figure 9 and 10
- Serialised into **RDF/XML (W3C SW)**, mapped to **RDF Triple Stores** – forms the agent’s belief base – 446 lines (Table 2)
- KB ready for querying to check truth of the agent’s beliefs
- Key Performance Indicators – representational and inferential adequacy

Figure 9 & 10– COGUI–Original KB of facts – graphically

Table 2 – Extract of a RDF triple Stores KB

No	Subject	Predicate	Object
1	http://www.lirmm.fr/cogui#t_ad452f18-e654-4ae6-b3a1-b7320616283b	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://www.w3.org/2000/01/rdf-schema#Class
2	http://www.lirmm.fr/cogui#t_fdc6d7d0-1314-4fb7-8428-51e122953250	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://www.w3.org/2000/01/rdf-schema#Class

12. Motivating – Dialogue Management

- Dialogue manager
- Missing information
- Pronoun resolution
- Discourse representation theory (DRS)
- Transition points
- Common ground (Stalnaker, 2002)

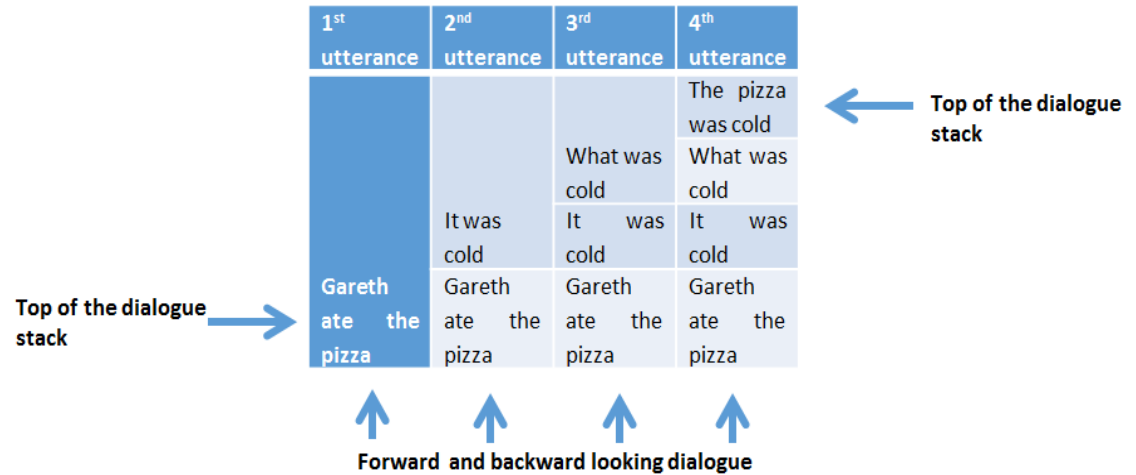


Figure 11 – Dialogue management & pronoun resolution (Panesar, 2017)

- Dialogue Handler:
- 2 types of responses
- (a) and (b)

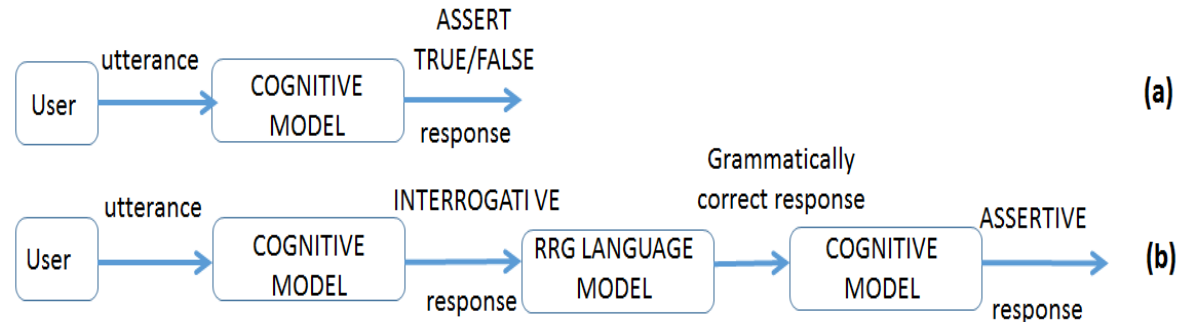


Figure 12– Agent Cognitive Model – message responses (Panesar, 2017)

13. Motivating Questions

A functional model of language, in particular Role and Reference Grammar (RRG), can underpin the linguistic model of a conversational software agent (CSA), at the interfaces of dialogue, knowledge and language (Panesar, 2017)

1. What are the component models of a linguistically motivated CSA?
2. How the model of belief, desires and intentions (BDI) might be characterised such that the mental model will interface with the RRG linguistic model, at the intersection of knowledge and language?
3. How do speech acts based on dialogue integrate with the RRG Model, Speech Acts, and BDI model and dialogue manager, within the context of conversation?
4. How will knowledge representation interface with the RRG Model, Speech Acts and BDI model to facilitate understanding of the utterance and the generation of a grammatically correct response?

14. Conceptual Framework: LING-CSA

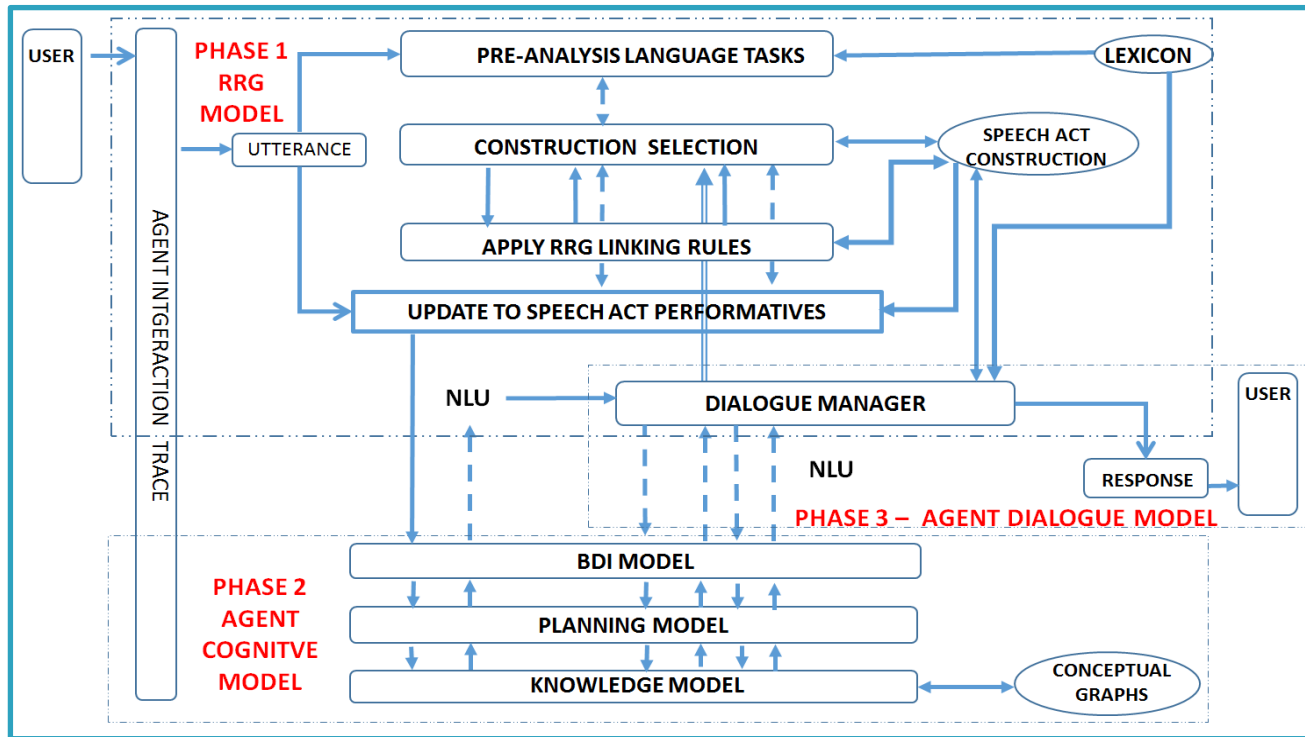


Figure 13 – Conceptual framework of the Conversational Software Agent (Panesar, 2017)

PHASE 1 – Role and Reference Grammar (RRG) Language Model

PHASE 2 – Agent Cognitive Model interfaces with:

BDI Model, Planning Model, Knowledge Model

PHASE 3 – Agent Dialogue Model (Dialogue Mgmt > RRG Model)

15. Phase 2 – Agent Cognitive Model Design Framework

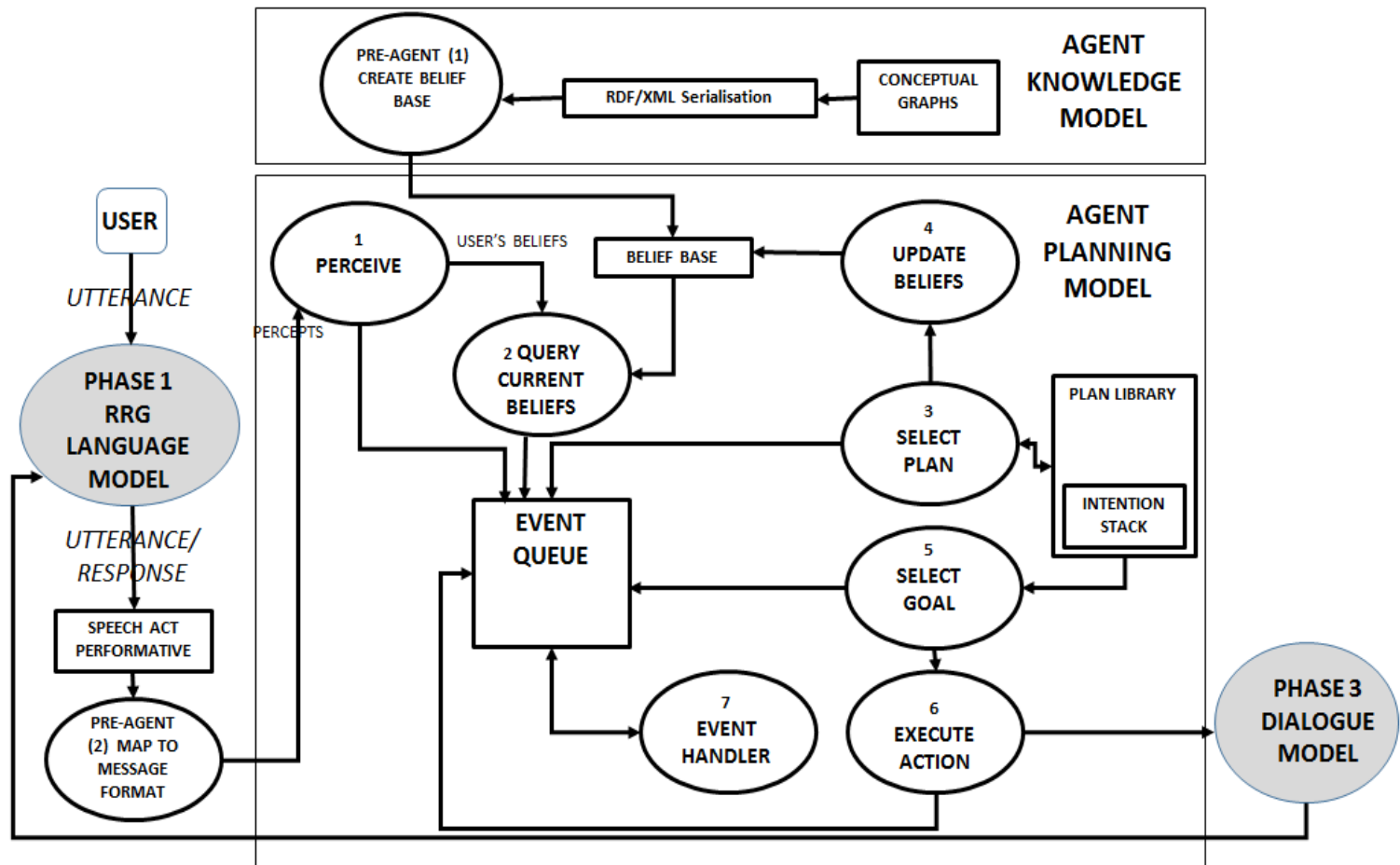


Figure 14- The Agent Cognitive Model - Design Framework (Panesar, 2017)

16. Implementations (Phase 1 – RRG Model)

- **Aim**– proof of concept and Java based prototype in Eclipse IDE
- Each specific construal (either an utterance or response) –two steps.
 1. Find the matching SA construction of that specific predicating element. In Figure 2: *'is'* and **selected SAC of assertive.**
 2. Select the matching signature pattern → **[PN, VBE, PRP, DET, N]**
- Updates > SAC first and extended SAP (Panesar, 2017)

```
<terminated> MainCAversion30 [Java Application] C:\Program Files (x86)\Java\jre1.8.0_101\bin\javaw.exe (22 Jun 2017)

*****
Syntactic representation of this utterance >>>>>
SENTENCE ( CLAUSE ( <CORE> <NP> gareth ( <NUC> ( <PRED> <AUX> is ) ) ( <PP>
in ( <NP> ( the restaurant ) ) ) ) ) )

*****

Speech Act Performative
*****

::::Performative =SAP ASSERTIVE IN ::::Sender =<USER>::::Receiver<AGENT::::ontology =
::::Signature =[PN VBE PRP DET N]::::Constraint =DEFAULT::::Input =gareth is in the
restaurant::::Workspace =[[gareth, PN], [is, VBE], [in, PRP], [the, DET],
[restaurant, N]]::::Syntax =SENTENCE ( CLAUSE ( <CORE> <NP> gareth ( <NUC> (
<PRED> <AUX> is ) ) ( <PP> in ( <NP> ( the restaurant ) ) ) ) ) :::: PSA
=gareth::::SemanticsRRG =NONE::::Linking =CONTAINS A NOUN PHRASE BEFORE AND AFTER THE
VERB::::Morphology =DEFAULT::::Pragmatics =TRUE/FALSE::::IllForce
=ASSERTIVE::::FocusStructure=NARROW FOCUS ON THE ELEMENT::::OutputLS
=<IF>ASS<TNS><PRT> be-in'(gareth,restaurant)
```

Figure 15 – Snapshot output of LING-CSA (Panesar, 2017)

17. Phase 1 – RRG & Speech Act Performative

Based on the SAC with four additional attributes. Input to Phase 2.

PERFORMATIVE: <ASSERTIVE:ATE>
:SENDER <USER>
:RECEIVER <AGENT-1>
:ONTOLOGY <FoodAndCookKB>
:CONTENT <do'(Gareth, (eat'(Gareth, pizza)))] & INGR consumed' (pizza)] everything>
SIGNATURE: [PN V NP ADJ]
CONSTRAINT: Default
INPUT: Gareth ate everything fast
WORKSPACE: (Gareth, PN), (ate, VERB), (everything N), (fast, ADJ)
SEMANTICS: Contains a noun phrase before and after the verb
CONSTRUCTION BODY
SYNTAX: SENTENCE (CLAUSE (<CORE> <NP> gareth (<NUC> (<PRED> <V> ate)) (<NP> (everything))) (PERIPHERY fast)
PSA: gareth
SEMANTICS
Linking:
MORPHOLOGY:Default
PRAGMATICS
Illocutionary force: ASSERTIVE
Focus structure: narrow focus on the element
OUTPUT [LS]: [<IF> ASS <TNS> PST, do'(ACT:Gareth, (eat'(Gareth <NOM>, pizza <ACC>)))] & INGR consumed' (UND:pizza)]

Table 3–Speech Act Construction Performative “ate” used as a message to the Agent Environment (Panesar, 2017)

18. Evaluations and Findings

Implementation outcomes :

- Dialogue Manager is common to Phase 1 and Phase 3

Testing:

- Grammatical tests, RRG specific tests
- Phase based and interfacing, intersection and integration tests

Findings proof-of-concept achieved; RRG is fit for purpose -> linguistic engine for the CSA; RRG explains, describes linguistic phenomena; facilitates language processing and knowledge of language -> computationally adequate (Panesar, 2017)

RRG Model Improvements:

1. All pronoun resolutions (E.g. 'Your', 'she', 'it' etc.)
2. Complex sentences (extension of the RRG linking system)
3. Multi-lingual (additional lexicons) such as Spanish
4. Other SA classes such as emotive and commissives E.g analyse tweets
5. Include superlative adjectives/adverbs in the RRG Lexicon (E.g. 'spicier')
6. Invoke WordNet API for synonymous entries to the RRG Lexicon - ↑value

Phase 2 Agent Cognitive Model working - 70% achieved Dialogue mgnt ✓

Technical Challenge - Querying a natural language (NL) text against a knowledge representation (KR) of RDF triples poses a significant semantic gap

Conceptual solution (lexical bridge, BDI parser and RDF parser) (Panesar, 2017)

Future research

- Single agent to multi-agent environment - an extended design framework
- Content creation - via machine learning algorithms

19. Lexical Bridging Solution (Panesar,2017)

Reduce this semantic gap, by “building a lexical bridge (LB)” between the NL semantic and ontology semantics, with an aim to capture more of the meaning, by attempting to ‘lexicalize the ontology’.

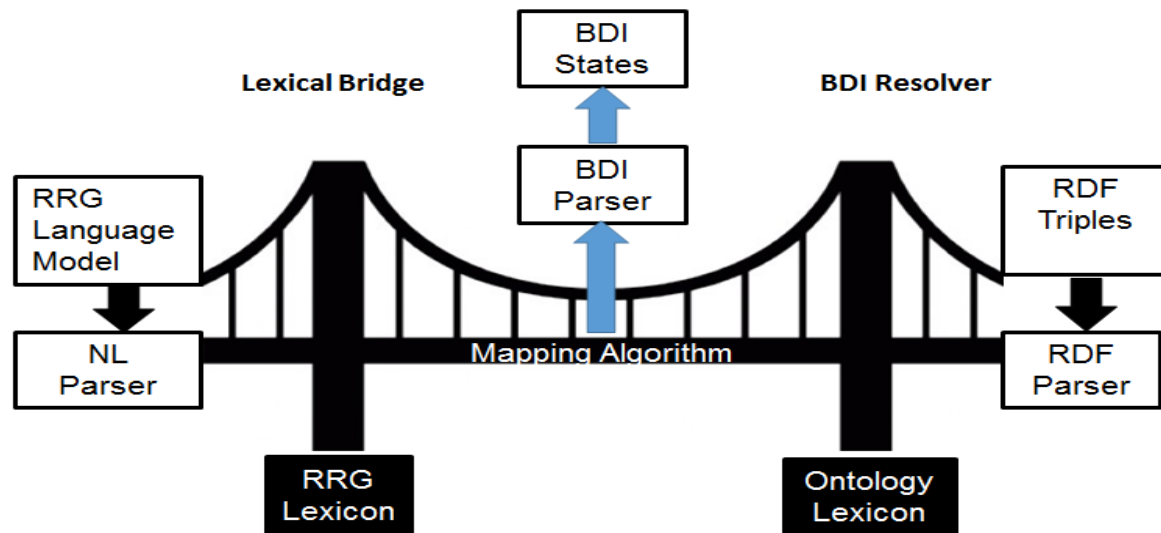


Figure 16 - Lexical Bridge for the CSA's belief base + BDI Parser to resolve the agent's BDI states

20. Contributions, Significance, Originality, and Conclusions (Panesar, 2017)

- **Contributions** – (1) extension of the theoretical and computational adequacy of RRG; (2) integration of RRG & SAC; (3) motivating of an agent framework based on RRG, cognitive model, dialogue model implemented as a proof of concept; (4) addresses the KR with RRG language model at the knowledge/language interface
- **Significance** – (1) delivers a linguistically motivated CSA (2) CSA is driven by a linguistic SA as a SAC; (3) SAC is an extension to the theoretical model of RRG; (4) interface (knowledge and language) is demonstrated; (5) agent behaviour (via the BDI model); (6) characterisations and challenges of one KR to another; (7) planning and intentionality are both common to the BDI model and SA links
- **Originality** – innovative and novel (integrate, interface and intersect)
- **Conclusions**
 - Motivations have been explored and contributions to knowledge.
 - Demonstrates the complexity of mapping lower level computations of natural language to an ontology – a natural language phenomena.
- **Challenge** – content creation and story comprehension (Wallace, 2018)

References

- Allen, J. (1995) *Natural Language Understanding (2nd Ed.)*. Benjamin-Cummings Publishing Co., Inc.
- Butler, C. S., and others (2008) *Layering in structural-functional grammars*. *Linguistics*, 46(4), pp. 689–756.
- Cohen, P. R. and Levesque, H. J. (1990) *Intention Is Choice with Commitment*. *Artificial Intelligence*, 42(2), pp.213–261.
- Gartner. 2015. *Market Trends: Voice as a UI on Consumer Devices — What Do Users Want?* [Online]. Available: <https://www.gartner.com/doc/3021226/market-trends-voice-ui-consumer> [Accessed December, 2017].
- Nolan, B. (2013) *Constructions as Grammatical Objects : A Case Study of Prepositional Ditransitive Construction in Modern Irish*. In: Nolan, B. and Diedrichsen, E. (Eds.): *Linking Constructions into Functional Linguistics: The Role of Constructions in Grammar*. Amsterdam/Philadelphia, John Benjamins Publishing Company, pp.143–178
- Nolan, B. (2014) *Extending a Lexicalist Functional Grammar through Speech Acts, Constructions and Conversational Software Agents*. In: Nolan, B., & Periñán-Pascual, C. (Eds.): *Language Processing and Grammars: The role of functionally oriented computational models*. Vol.150. John Benjamins Publishing Company, pp.143–163.
- Panesar, K. (2017). *A linguistically centred text-based conversational software agent*. Unpublished PhD Thesis. School of Computing, Creative Technologies and Engineering. Leeds, UK, Leeds Beckett University.
- Periñán-Pascual, C. (2013) *A Knowledge-Engineering Approach to the Cognitive Categorization of Lexical Meaning*. *VIAL-VIGO INTERNATIONAL JOURNAL OF APPLIED LINGUISTICS*, 10, pp.85–104.
- Rao, A. S. and Georgeff, M. P. (1995). *BDI Agents: From Theory to Practice*. Paper presented at the ICMAS.
- Searle, J. R. (1969) *Speech Acts: An Essay in the Philosophy of Language*. Cambridge University Press.
- Sowa, J. F. and Way, E. C. (1986) *Implementing a Semantic Interpreter Using Conceptual Graphs*. *IBM Journal of Research and Development*, 30(1), pp.57–69.
- Van Valin, R. D. (2005) *Exploring the Syntax-Semantics Interface*. CUP..
- Pokahr, A., Braubach, L., Haubeck, C. and Ladiges, J. (2014) *Programming BDI Agents with Pure Java*. In: *Multiagent System Technologies*. Springer, pp.216–233
- Wallace, R. 2018. *Chatbots – a personal perspective*. *Society for the study of Artificial Intelligence and Simulation of Behaviour (AISB) quarterly*, 6.
- Visualistan, 2017. *Chatbots: The Good, The Bad And The Ugly* [Online]. Available: <https://www.visualistan.com/2017/10/chatbots-good-bad-and-ugly-infographic.html> [Accessed Feb 2018]
- Wooldridge, M. (2013) *Intelligent Agents*. In: Weiss, G. (Ed.): *Multiagent Systems*. USA, Massachusetts Institute of Technology, pp.3–50.

Thank you for listening!