INTERACTION LAB

HERIOT WATT UNIVERSITY

LET'S DISCUSS: LEARNING METHODS FOR DIALOGUE
NIPS 2016 WORKSHOP, December 10th, 2016, Barcelona, Spain

Awkward Silence?
The Evaluation of Social Dialogue Systems

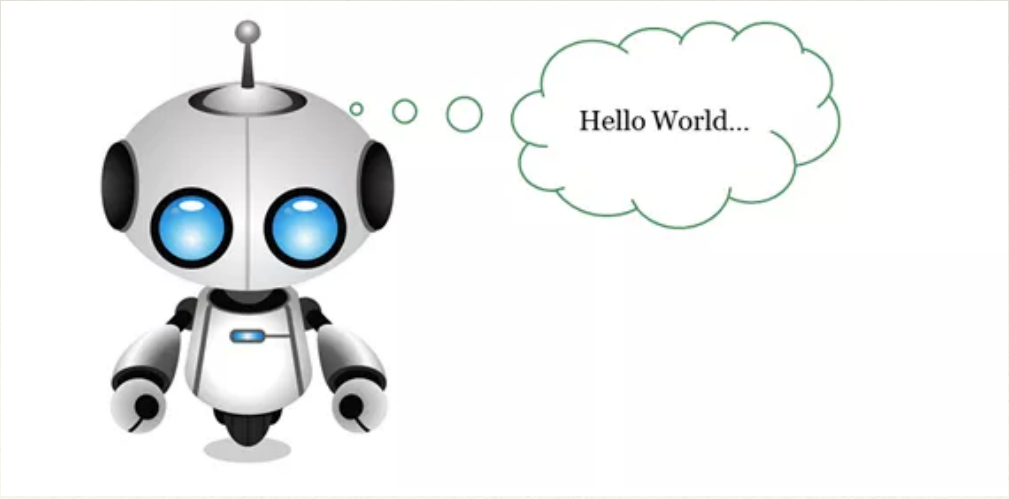
Helen Hastie
Heriot-Watt University,
Edinburgh

Overview

- What are Social Dialogue Systems (aka Social Chatbots) and why are they so tricky to evaluate?
- Survey of current evaluation metrics
- What can we learn from other disciplines?
  - gaming, HCI, psychology, robotics and cognitive theory
- Ethics
- Conclusion and summary

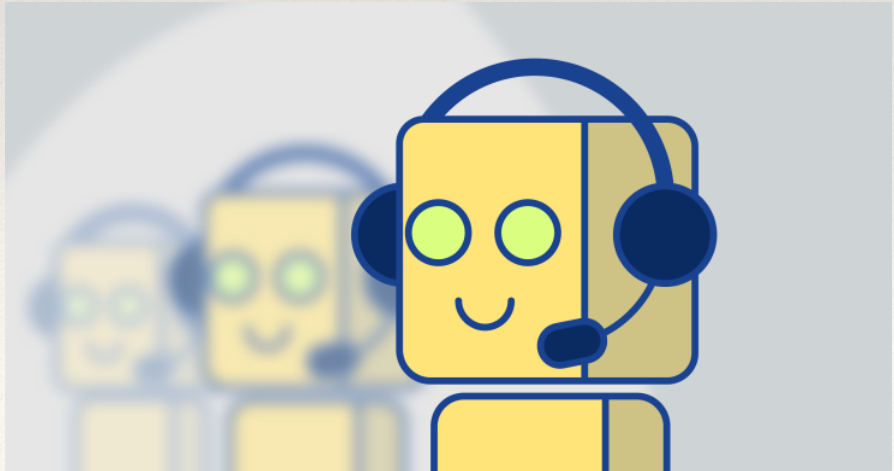
What is it?

- A Social Dialogue System/Chatbot is designed to engage humans on topics of interest,
- generate interesting, coherent, meaningful responses,
- carry on as long as possible,
- be a companion.



What's the point of them?

- Provides relevant information (What do I need to know?)
- Supports decision making (What should I do?)
- Facilitates action (How do I do something?)
- Keeps you company (I'm lonely I want to talk)



It's good to talk

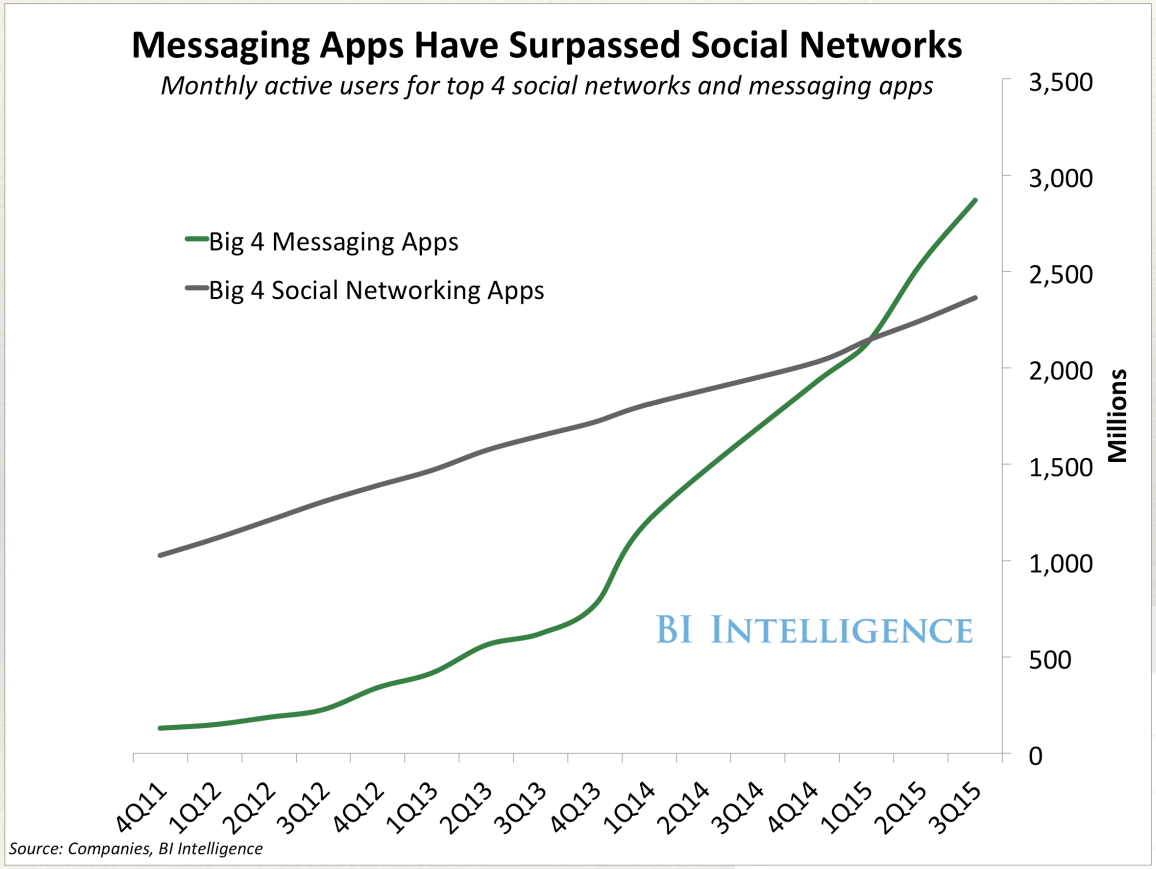
- Interactive system as a companion (Wilks, 2006)

A system by any other name

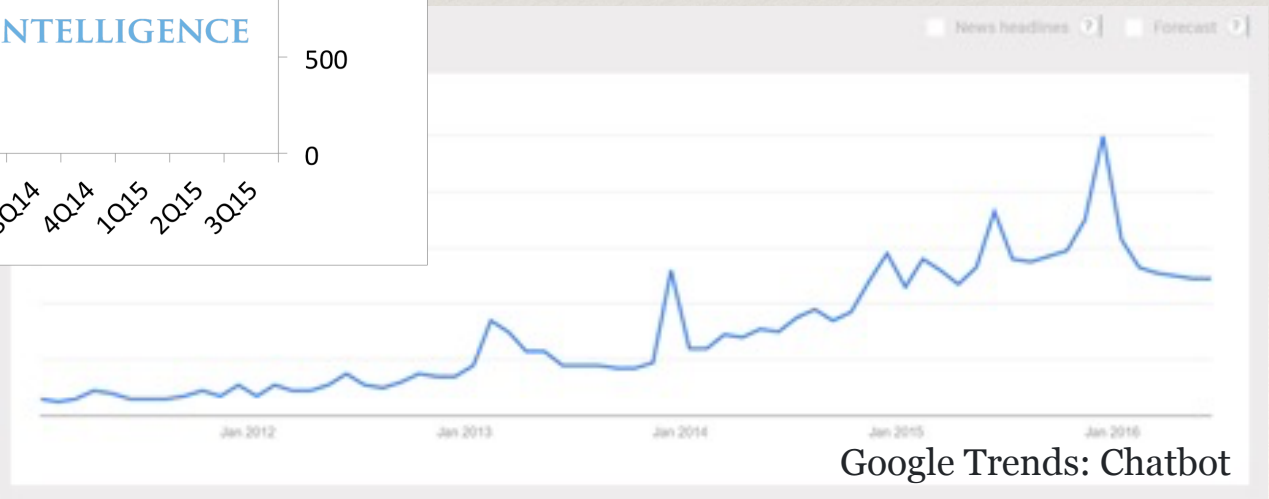
- (Neural) Response generation
- Unsupervised dialogue systems
- Interactive CA
- End-to-end CA
- Response Retrieval
- Example-based dialogue systems
- Next Utterance Classification

- Chatterbot
- Dialogue chatbot
- Chatbot
- AI bot
- Socialbot
- Social Media Bot
- Social chatbot

Why all the fuss?



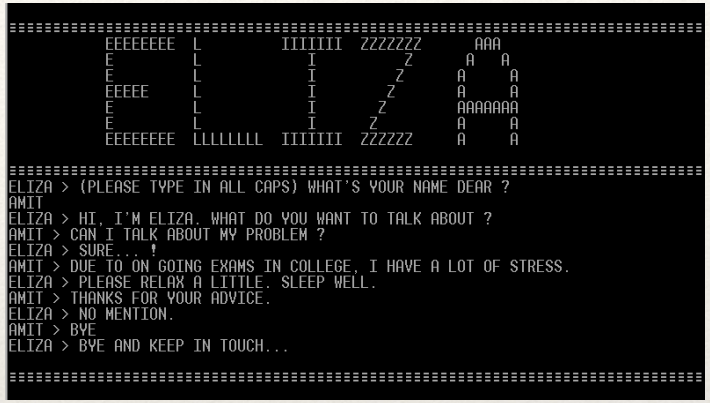
Bots are the new apps



Google Trends: Chatbot

Challenge: build a socialbot that can converse coherently and engagingly with humans on popular topics for 20 minutes.

Types of systems: rule based



- Eliza (Weizenbaum, 1966)
- Cobot in lambda moo (Isbell et al., 2000)
- A.L.I.C.E (Wallace, 2008)- using AIML
- Jabberwocky (Carpenter)
- Pandorabots (Mitsuku)

Types of systems: data-driven

1. **Response generation systems** that attempt to produce, word-by-word, a likely response given a conversational context using
    - e.g. (Deep) Neural Processing Models (Vinyals and Le, 2015, Shang et al., 2015, Li et al., 2016).
2. **Retrieval-based systems** that attempt to select a response from a (possibly large) list of utterances in a corpus
    - e.g. Next Utterance Classification (Lowe et al., 2016)
3. **The statistical machine translation** (SMT) based method
    - e.g. (Ritter et al., 2011).

Performance

Interaction quality

Coherence

Informative

EVALUATION

Humous

Fun

Enjoyment

Conversational Depth

Chatty

Diversity

Acceptability

Usability

Appropriateness

Information Flow

Extrinsic vs Intrinsic

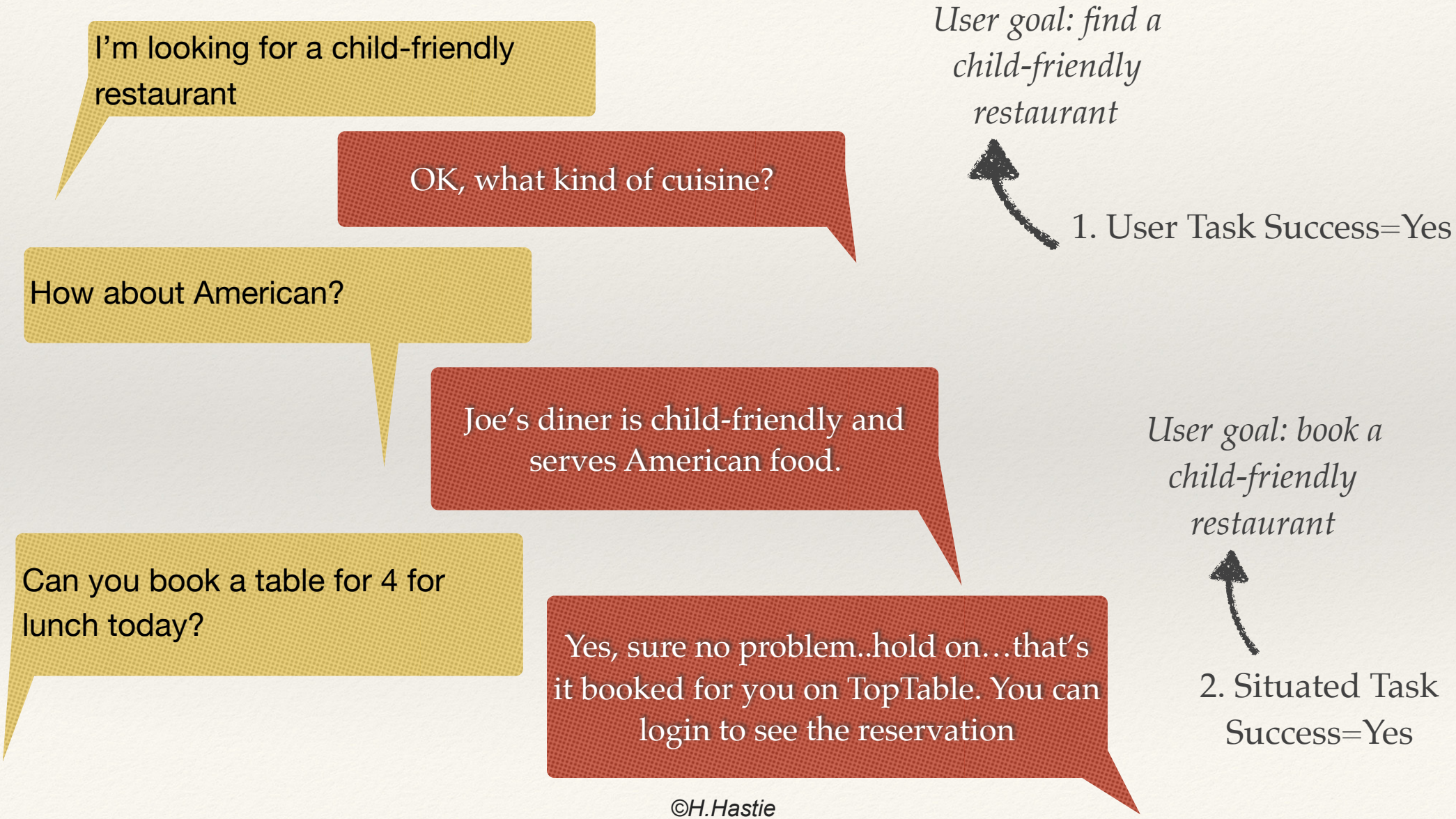
- **Extrinsic evaluations** assess the effect of a system on something that is external to it, in the real world
  - Task Success i.e. fulfils a user goal (e.g. book flights, find a restaurant)
- **Intrinsic evaluations** assess properties of systems in their own right
  - Automatic, e.g. BLEU
  - Hand-labelled, e.g. appropriateness, fluency

Redefining 'Extrinsic'

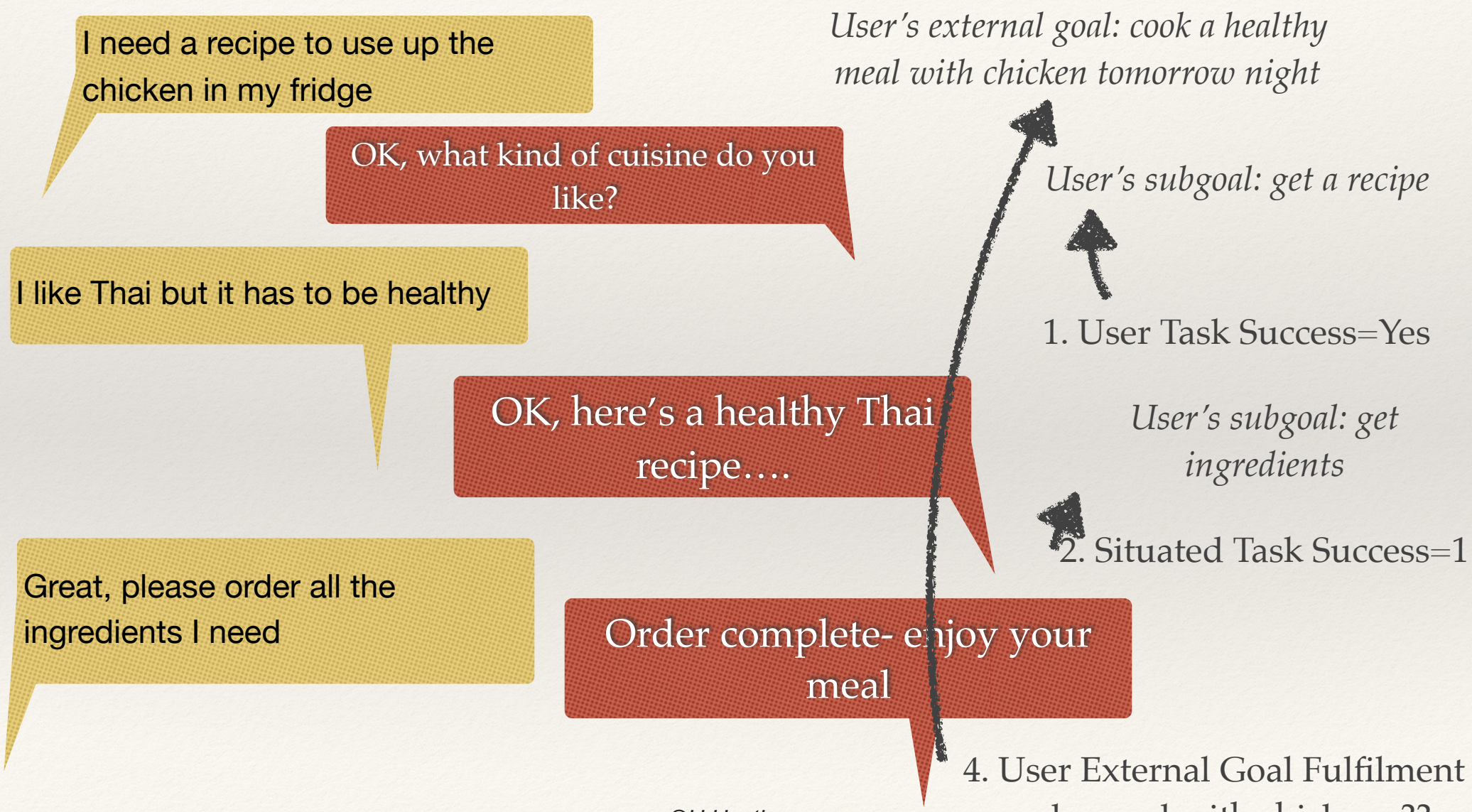
1. **User Task Success**
   - i.e. system helps the *user perform* a task through interaction (e.g., find restaurant information, find information on hotels, find treasure by giving instructions (GIVE))
2. **Situated Task Success**
   - i.e. system fulfils a user's situated goal by *performing an action* e.g. through 3rd party service provider (e.g. books flights, books restaurants, orders flowers)
3. **User Internal Goal Fulfilment***
   - i.e. system helps user to fulfil their *internal goal through interaction* (e.g. discuss politics, learn French, cheer themselves up by chatting)
4. **User External Goal Fulfilment***
   - i.e. system helps the user to fulfil their *external goal outside of the interaction* (e.g. cook a meal in the evening, finish their essay)

*new to the socialbot era

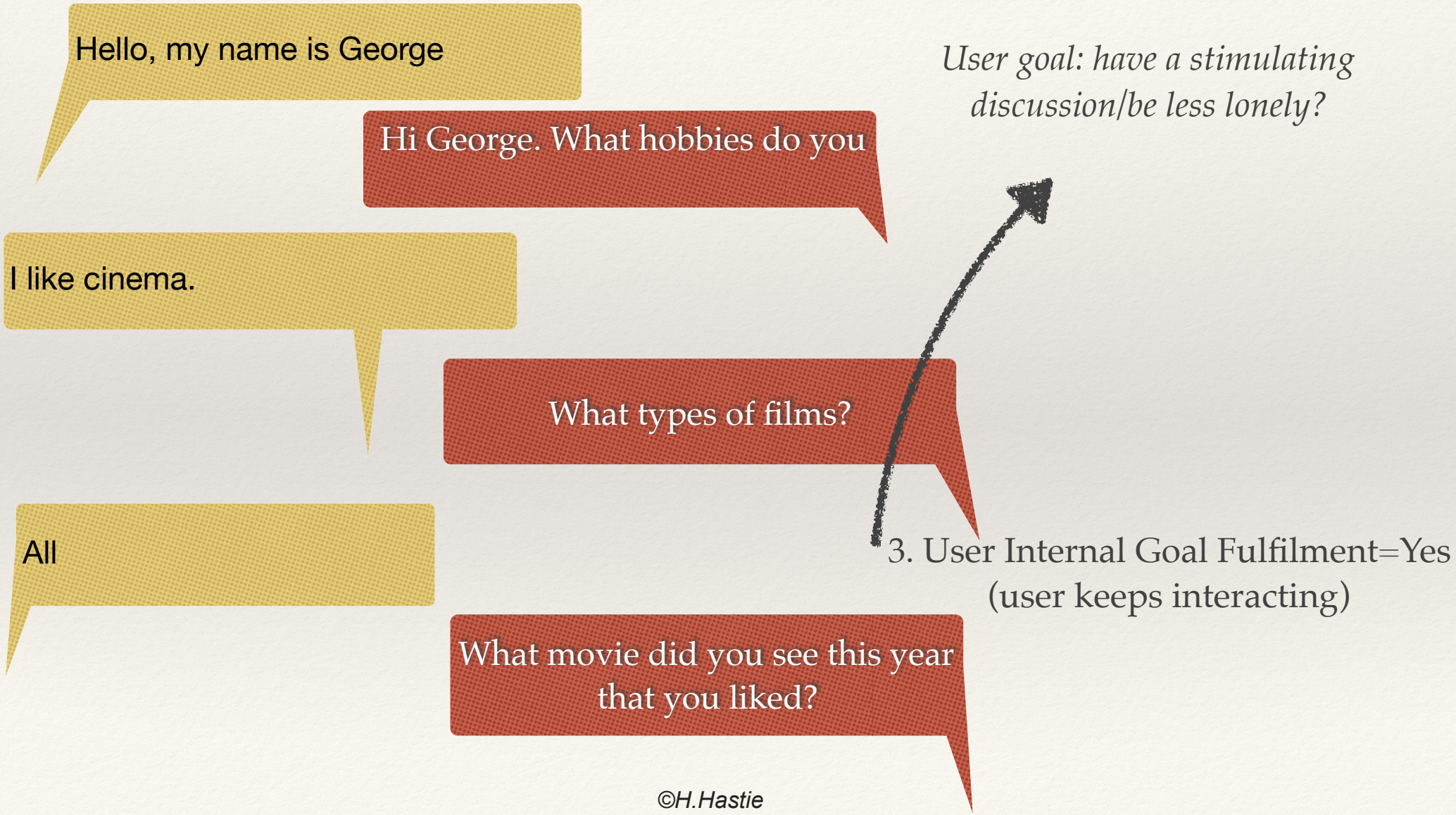
Ex. User and Situated Task Success



Ex. User External Goal Fulfilment



Ex. User Internal Goal Fulfilment



Redefining 'Extrinsic'

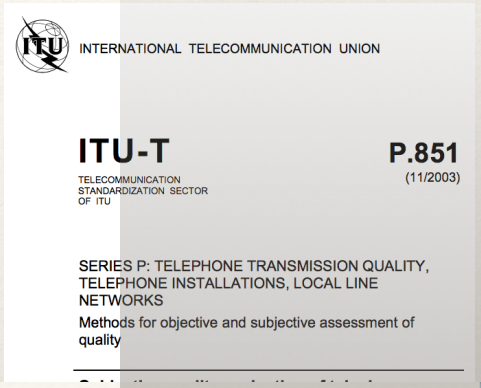
1. **User Task Success**
   - i.e. system helps the *user perform* a task through interaction (e.g., find restaurant information, find information on hotels, find treasure by giving instructions (GIVE))
2. **Situated Task Success**
   - i.e. system fulfils a user's situated goal by *performing an action* e.g. through 3rd party service provider (e.g. books flights, books restaurants, orders flowers)
3. **User Internal Goal Fulfilment***
   - i.e. system helps user to fulfil their *internal goal through interaction* (e.g. discuss politics, learn French, cheer themselves up by chatting)
4. **User External Goal Fulfilment***
   - i.e. system helps the user to fulfil their *external goal outside of the interaction* (e.g. cook a meal in the evening, finish their essay)

How measure?

How measure?

*new to the socialbot era

Evaluation Frameworks

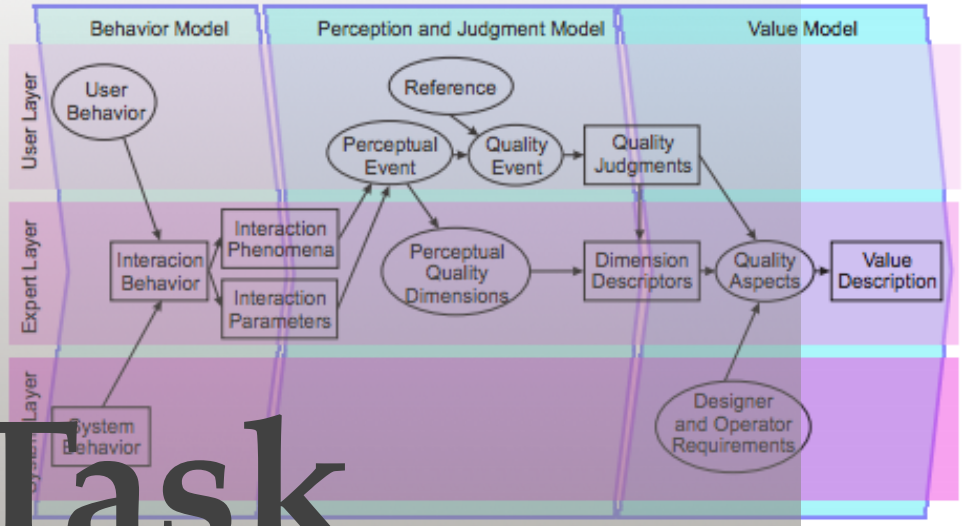

INTERNATIONAL TELECOMMUNICATION UNION

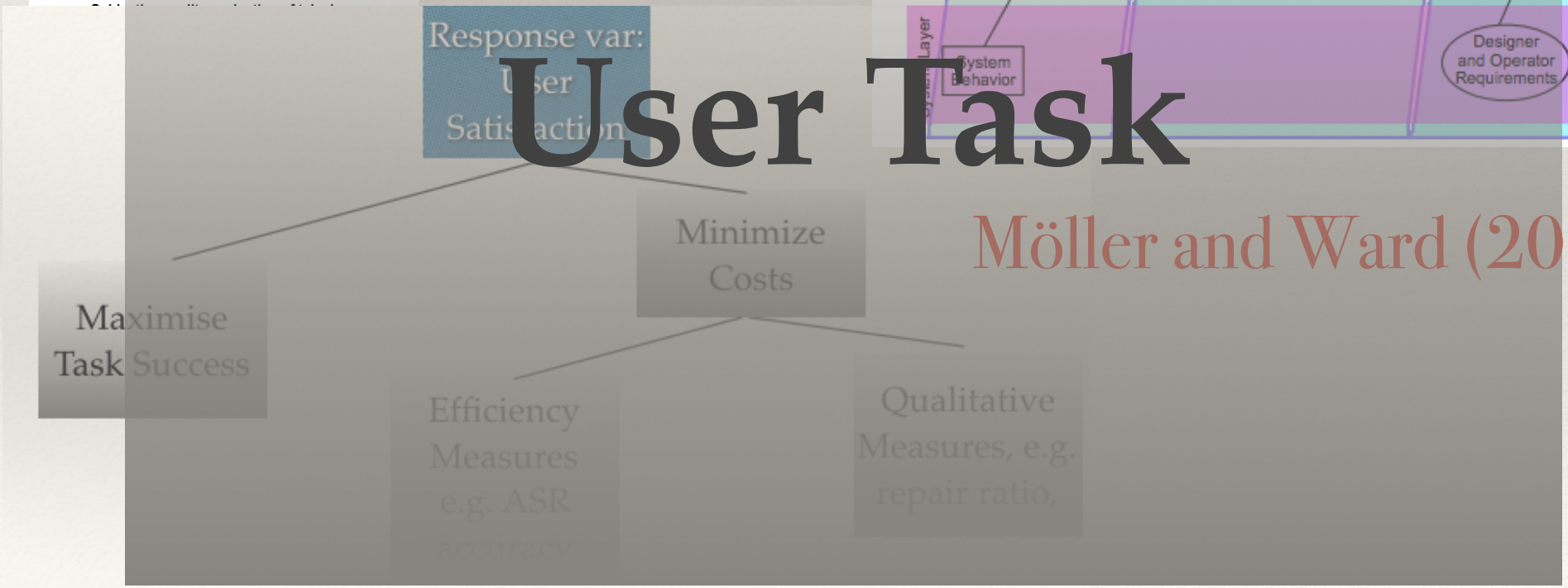
ITU-T P.851 (11/2003)

TELECOMMUNICATION STANDARDIZATION SECTOR OF ITU

SERIES P: TELEPHONE TRANSMISSION QUALITY, TELEPHONE INSTALLATIONS, LOCAL LINE NETWORKS

Methods for objective and subjective assessment of quality





User Task

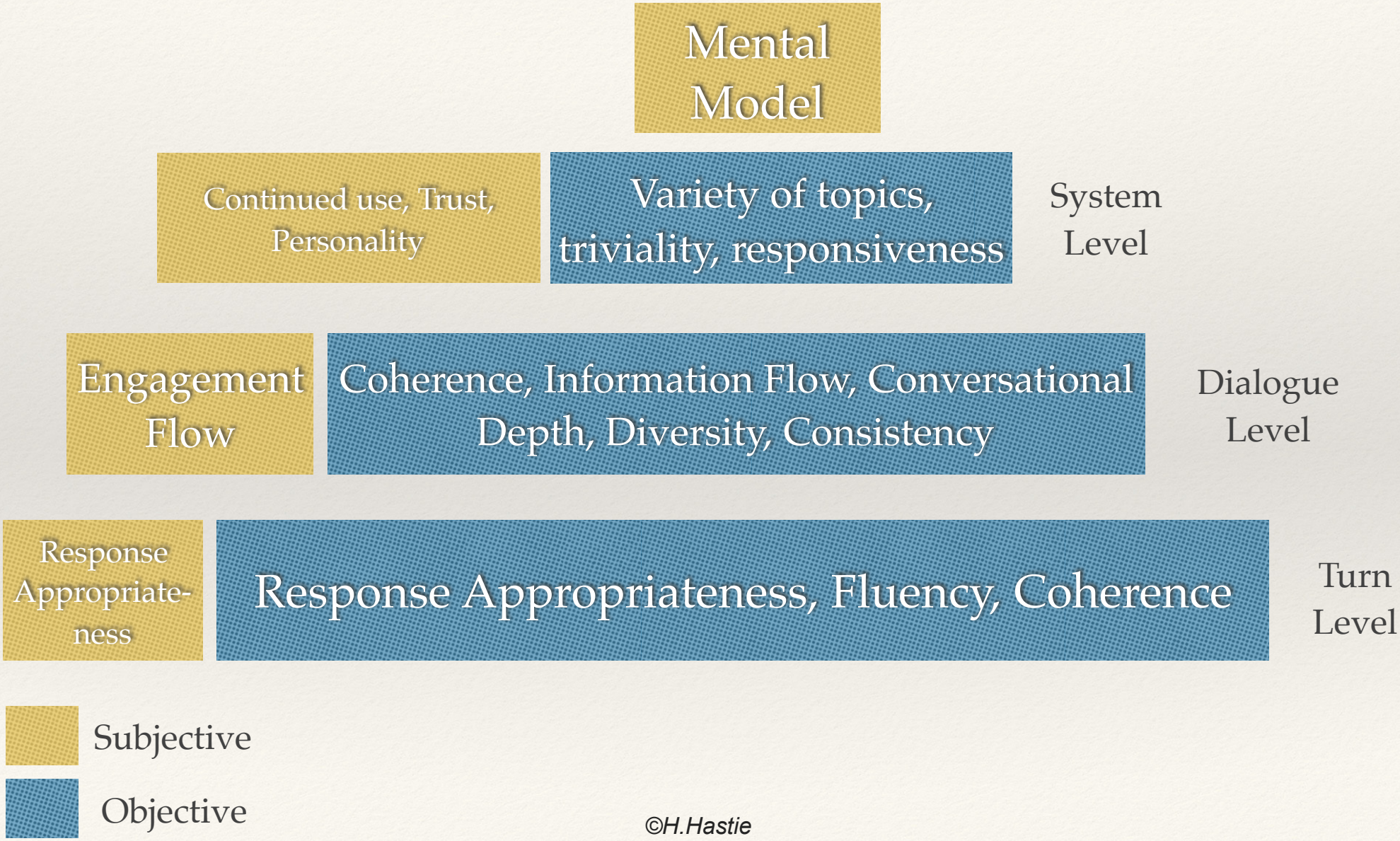
Möller and Ward (2008)

PARADISE (Walker et al., 1997)

Metrics by Approach

Approach	Human	Automatic	Estimated
Generative Approaches	Pairwise comparison (Li et al. 2016a, Vinyals & Le, 2015); next utterance rating; 5 turn 3rd party rating (Li et al., 2016b)	Diversity (Li et al. 2016a); BLEU, DeltaBLEU; Length metrics; Perplexity (Vinyals & Le, 2015); ROUGE (Xu et al., 2016); METEOR (Sordoni et al., 2015)	Appropriateness; Conversational depth; Information gain (Yu et al., 2016a)
Retrieval (NUC)	Pairwise comparison (Lowe et al., 2016)	Recall (Kaldec et al., 2015, Lowe et al., 2016); Precision (Al-Rfou et al., 2016)	
SMT	Pairwise comparison (Ritter et al., 2011)	BLEU (Ritter et al., 2011)	
WoZ	User Engagement, User engagement change, appropriateness (Yu et al., 2016b)	Count of mitigation strategies used (Yu et al., 2016b) .	

Evaluation Hierarchy



Evaluation Hierarchy

TURN LEVEL SUBJECTIVE
Response Relevance / Appropriateness

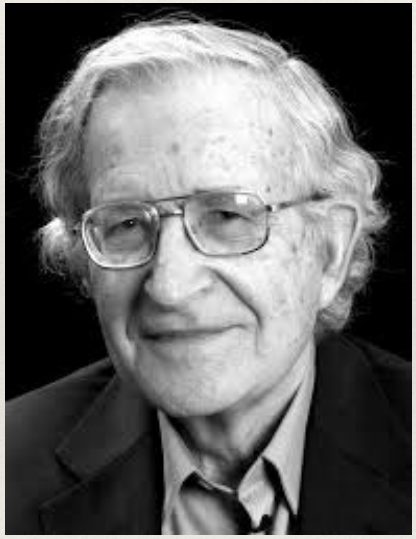
Example
Participant: How old are you? *TickTock*: Apple.
Participant: How old are you? *TickTock*: That's too big a question for me to answer.
Participant: How is the weather today? *TickTock*: Very good.

Appropriateness human-annotation (Expert) *Kappa= 0.73* (Yu et al., 2016b)

TURN LEVEL SUBJECTIVE
Response Relevance / Appropriateness

- **Appropriateness/coherence with user utterance**
  - Ratings (Webb, 2010, Sordoni et al., 2015, Shang et al., 2015, Yu et al., 2016b)
  - Pairwise Comparison (Ritter et al., 2011, Li et al. 2016a, Vinyals & Le, 2015, Lowe et al., 2016)
- Other **Intrinsic measures**
  - Naturalness (Shang et al., 2015),
  - Fluency (Serban et al., 2016)
  - Adequacy / Clarity of reference (Li et al., 2016b)
  - Informativeness (Wen et al., 2015)

Expert vs Turkers vs Customers



TURN LEVEL OBJECTIVE
Response Appropriateness, Fluency, Coherence

- Challenges
  - Non-constrained dialogues,
  - No ‘one answer’: multiple ‘good’ responses (Sordoni et al., 2015),
  - Need to take into account the context of the turn/ conversation.

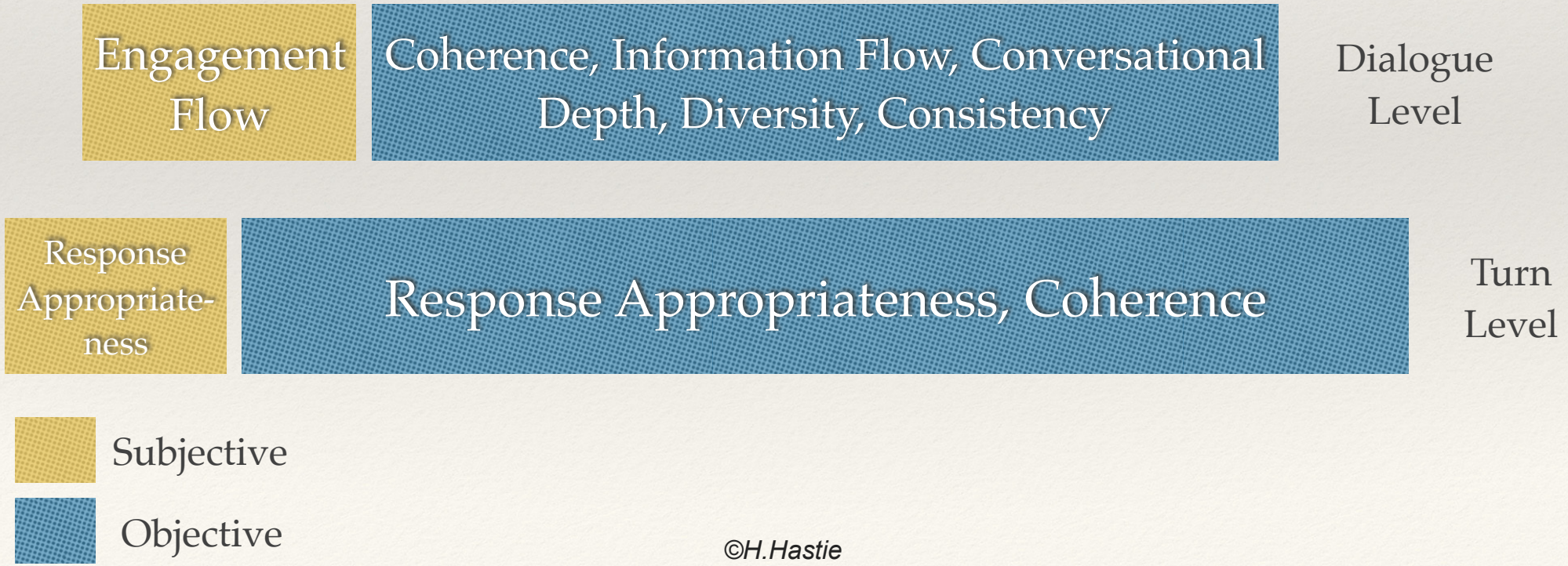
TURN LEVEL OBJECTIVE
Response Appropriateness, Coherence

- Comparative metrics
  - BLEU, DeltaBLEU (Ritter et al., 2011, Liu et al., 2016); ROUGE (Xu et al., 2016); METEOR (Sordoni et al., 2015)
  - Perplexity (Vinyals & Le, 2015)
- Information Retrieval Metrics
  - Recall (Kaldec et al., 2015, Lowe et al., 2016)
  - Precision (Al-Rfou et al., 2016)

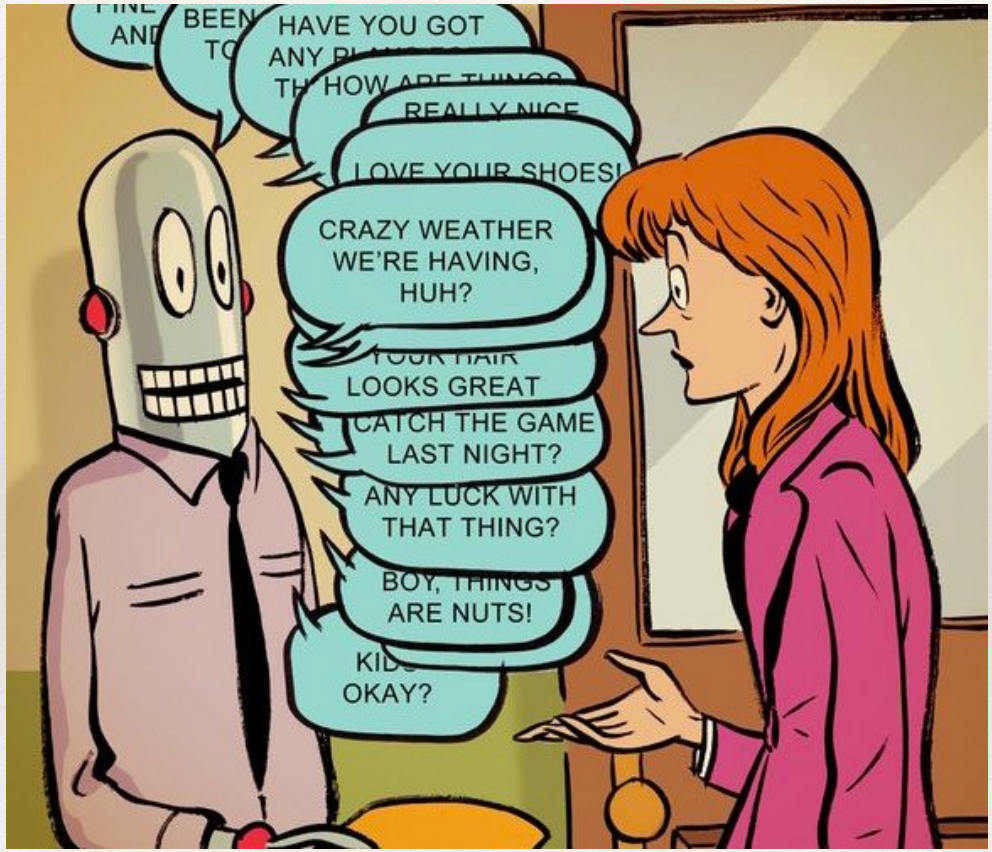
TURN LEVEL OBJECTIVE
Response Appropriateness, Coherence

- Coherence: semantic/syntactic similarity metrics between user-system turn (Yu et al. 2016a)
- Confidence score (e.g. posterior probability for NN) (Yu et al., 2016a)
- Length metrics
- Approximating subjective ratings,
  - e.g. response appropriateness (73% accurate) via a classifier (Yu et al., 2016a)

Evaluation Hierarchy



DIALOGUE LEVEL SUBJECTIVE
Engagement, Flow



"By engagement, we mean the process by which two (or more) participants *establish*, maintain and end their perceived *connection*. This process includes: initial contact, negotiating a collaboration, checking that other is still taking part in the interaction, evaluating whether to stay involved, and deciding when to end the connection. "

– Sidner, C. L., Kidd, C. D., Lee, C., & Lesh, N. (2003). Where to Look: A Study of Human-Robot Engagement. In ACM International Conference on Intelligent User Interfaces (IUI)

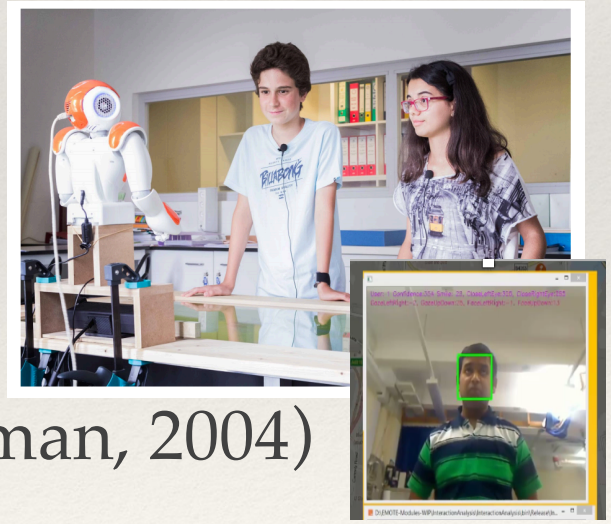
Engagement in Social Robotics

- Detect user affect including engagement and adapt interaction
- Robots have the advantage of :
  - having vision multiple modalities to detect engagement e.g. face, body, gesture, speech (Castellano et al., 2008), gaze (Sidney et al. 2003)
  - having language and gesture to mitigate disengagement

Engagement in Intelligent Tutoring Systems

- Engagement leads to motivation which leads to greater learning gain
- Detect affect and adapt pedagogical strategies/interaction
  - e.g. frustration, boredom (Castellano et al., 2013; Litman and Forbes, 2003)
- ITS have the advantage of:
  - having progress on a task as an

    indicator of engagement (Litman and Sillman, 2004)



Engagement as an Evaluation Measure

- Hand-annotated (1st person or third person) per turn or across whole dialogue (Yu et al., 2016b)
- Speech
  - Emotion recognition using speech using toolkits, e.g. OpenSSI, OpenEar, Multisense (Yu et al., 2015)
  - Fluency of interaction as indicators of engagement/ attention e.g. user disfluencies, repairs, repetition (Shriberg, 1994)
- Language only: sentiment analysis

Engagement as reward signal

- Detect when we are successful in engaging the user and reinforce this behaviour using (Deep) Reinforcement Learning
  - Yu et al. (2015) maximise for Engagement as detected by MultiSense emotion recognition

Engagement and Flow

- Concept of Flow (named by Csíjszentmihályi)
  - is the mental state of operation in which a person performing an activity is fully immersed in a feeling of energized focus, full involvement, and enjoyment in the process of the activity.

Engagement and Flow cont.

- One must be involved in an activity with a clear set of *goals* and *progress*. This adds direction and structure to the task.
- The user should have clear and immediate feedback- allows them to adjust *their performance* to maintain the flow state.
- One must have *confidence* in one's ability to complete the task at hand. (Csíjszentmihályi et al., 2005)

Social system should support the user in his/her goal, give feedback/progress and increase user confidence

Engagement and Personalisation

- One way to make the user feel *involved* in the interaction and maintain flow is through personalisation
- Detect user style and adapt by matching linguistic style and lexical entrainment (Deutsch and Pechmann, 1982)

Personalisation in systems

- Rami Al-Rfou (2106) include the author ID in their response ranker to improve precision
- A Persona based Neural Model (Li et al., 2016c) performs entrainment and adaptation based on clusters of users (e.g. the system will respond to Brits differently to Americans).

DIALOGUE LEVEL SUBJECTIVE: Engagement, Flow

- Summary: How do we make systems more engaging?
  - Detect disengagement and adapt, e.g. through RL
  - Try to create Flow by making the user feel *involved* in the interaction
  - Personalisation may help keep users engaged

DIALOGUE LEVEL OBJECTIVE
Coherence, Information Flow, Conversational Depth, Diversity,

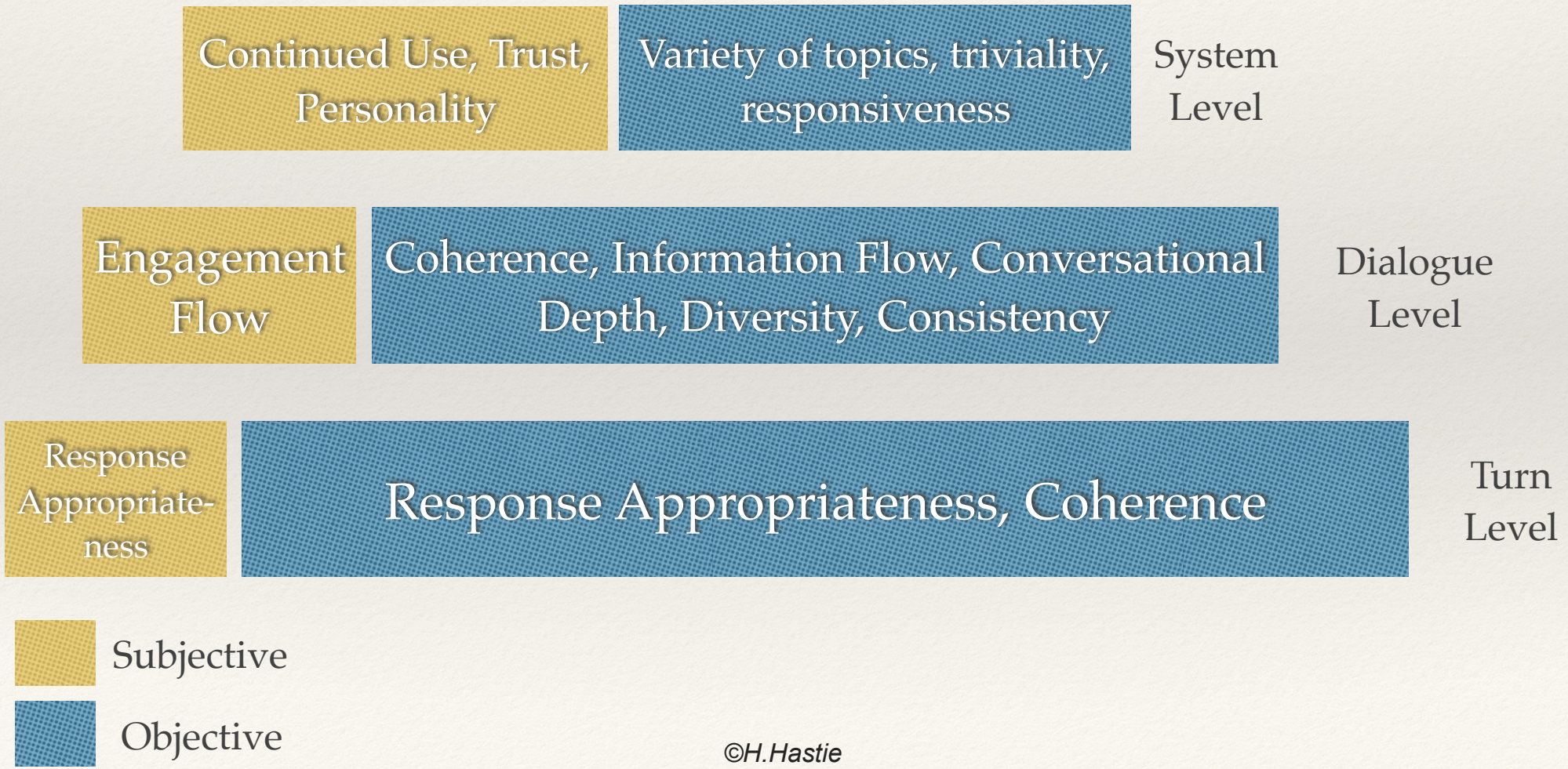
- **Information gain/flow**
  - e.g. number of unique words that are introduced into the conversation from both the system and the user. (Yu et al., 2016a)
  - *e.g. semantic dissimilarity between consecutive system turns (Li et al. 2016b)
- ***Semantic coherence** e.g. mutual information throughout dialogue (Li et al. 2016b)
- ***(System) Ease of answering, e.g.** negative log likelihood of responding to that utterance with a dull response (Li et al. 2016b)

**used in reward function for DRL (Li et al. 2016b)*

DIALOGUE LEVEL OBJECTIVE
Coherence, Information Flow, Conversational Depth, Diversity,

- **Conversational depth** e.g. a classifier using as features the number of consecutive utterances that share the same topic (kappa = 0.45)- 73% (Yu et al., 2016a)
- **Diversity of responses** e.g. number of distinct unigrams and bigrams (Li et al., 2016b)

Evaluation Hierarchy

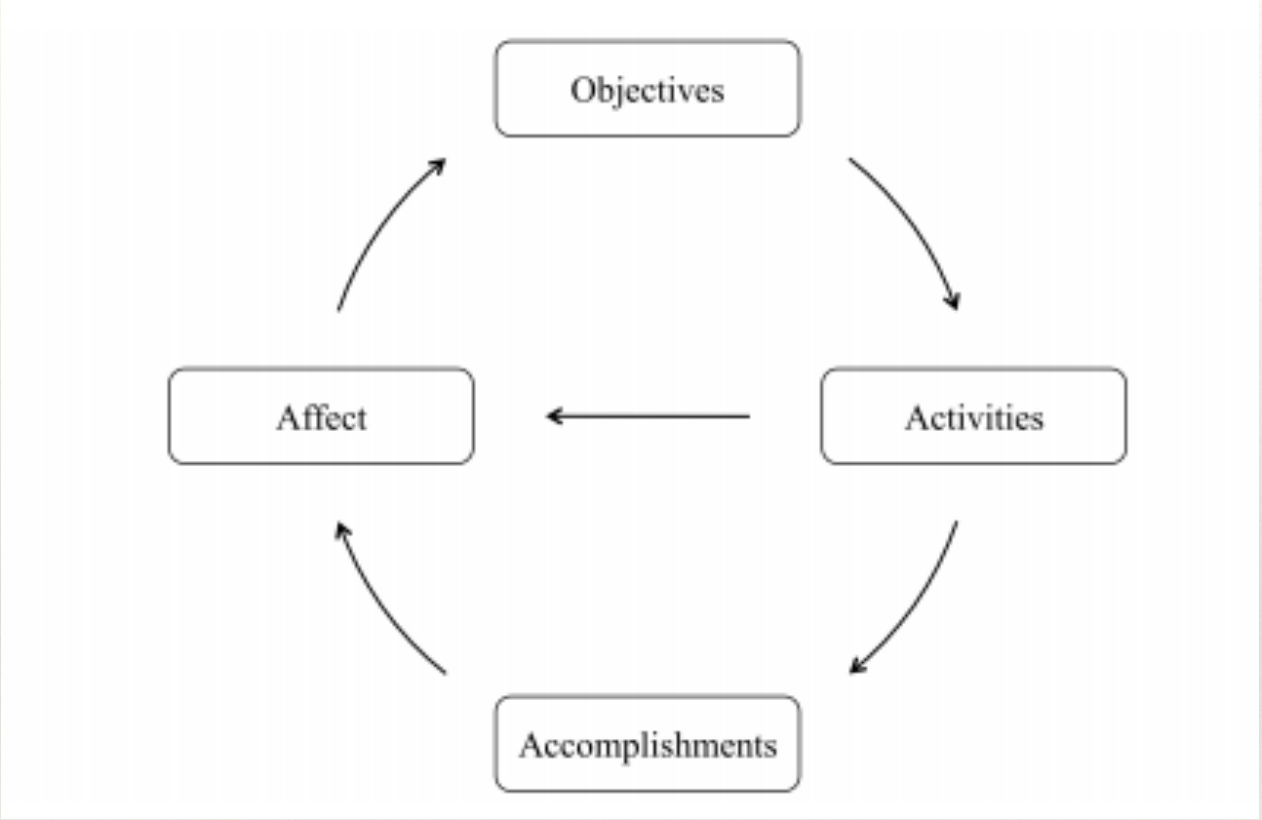


SYSTEM LEVEL SUBJECTIVE
Continuation Desire e.g. by repeated use

- Successful computer games have remarkable capability to:
  - draw people in (Jennett et al. 2008),
  - glue people to the game (Rigby and Ryan 2011), and
  - make people want to keep playing (Brown and Cairns 2004)

CONTINUATION DESIRE

SYSTEM LEVEL SUBJECTIVE
Continuation Desire (Schoenau-Fog, 2011)



Key aspects are

- activities: interaction with game interface including absorbed in a story
- accomplishments: feeling of progression, completion

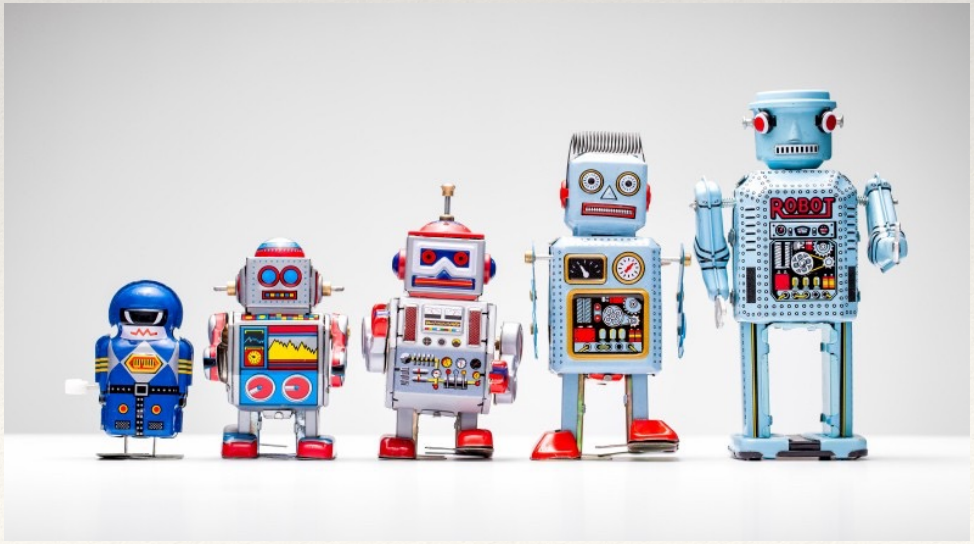
SYSTEM LEVEL SUBJECTIVE TRUST

- To continue using the system you have to trust it. Consensus that *Trust* is multi-dimensional
  - e.g. seriousness, controllability, security, privacy and transparency (Liechtenstein et al. , 2009)
- Certain utterances make trigger increase/decrease in trust (Lumsden, 2009)
- Explanations can help increase transparency and also therefore trust (Lim et al., 2009)

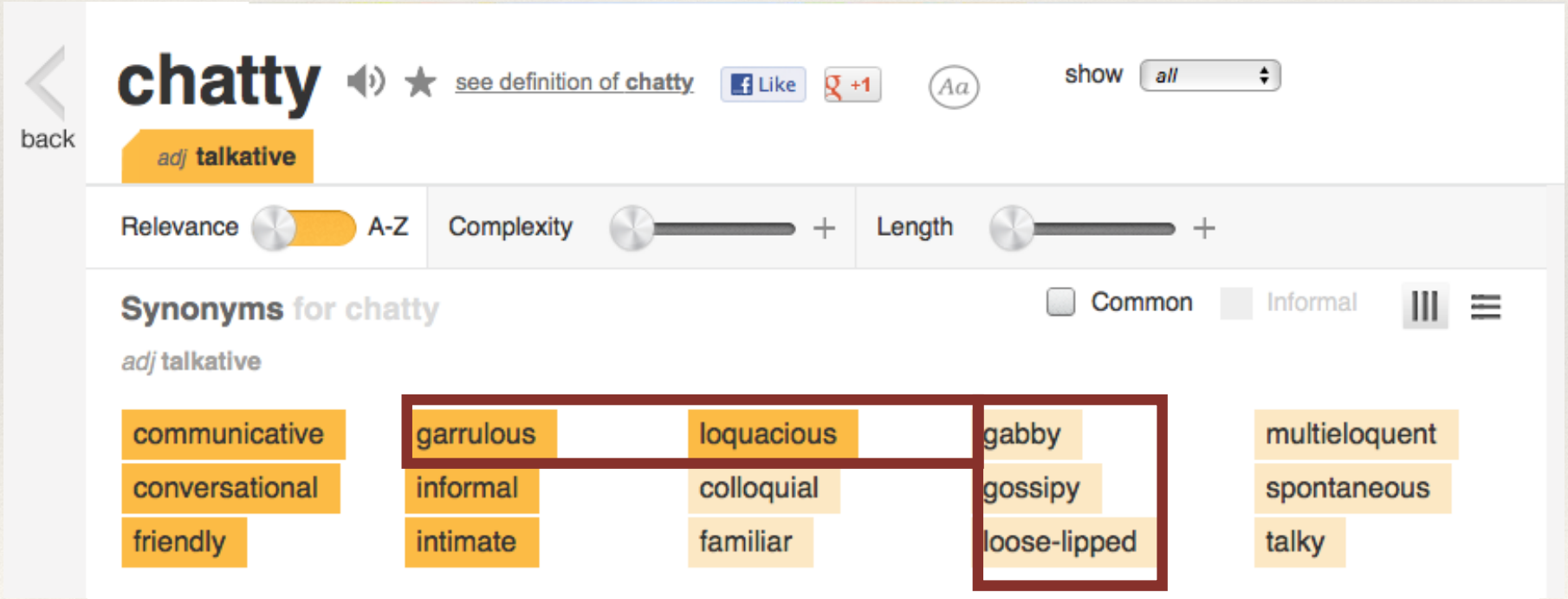
Include explanations in social system to increase trust?

SYSTEM LEVEL SUBJECTIVE
Personality

- User's perception of the system's personality can affect their subjective ratings



SYSTEM LEVEL SUBJECTIVE
Personality

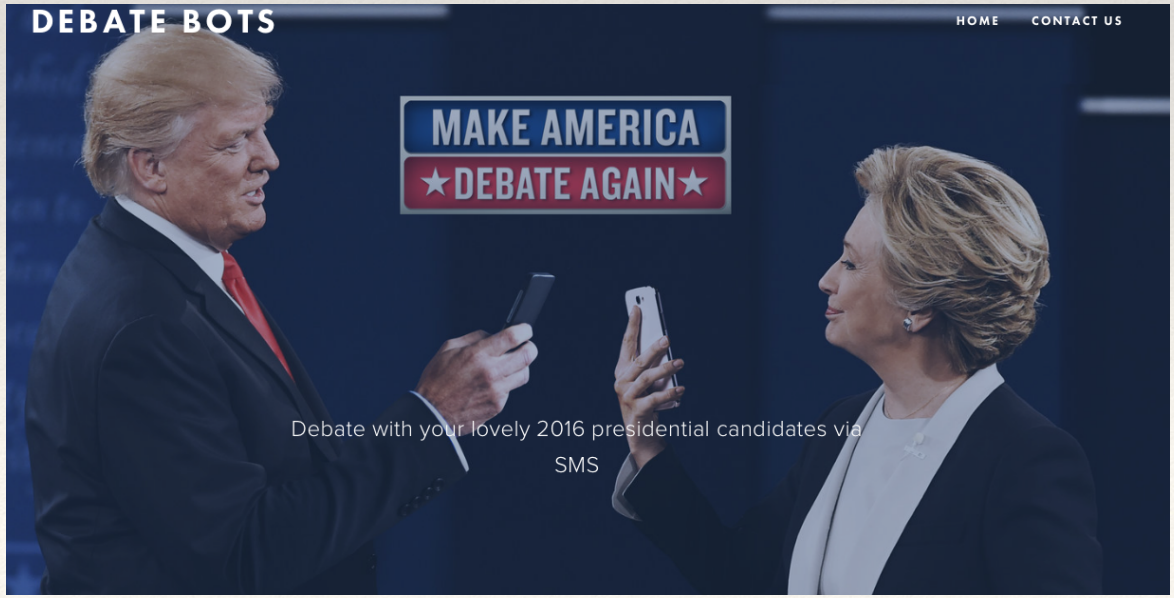


What if Hillary and Donald were chatbots?

“On the one hand, you have an erratic, defective bot that keeps going off topic while throwing tantrums and repeating the same buzzwords over and over again. And he does it in a surprisingly hypnotizing fashion.

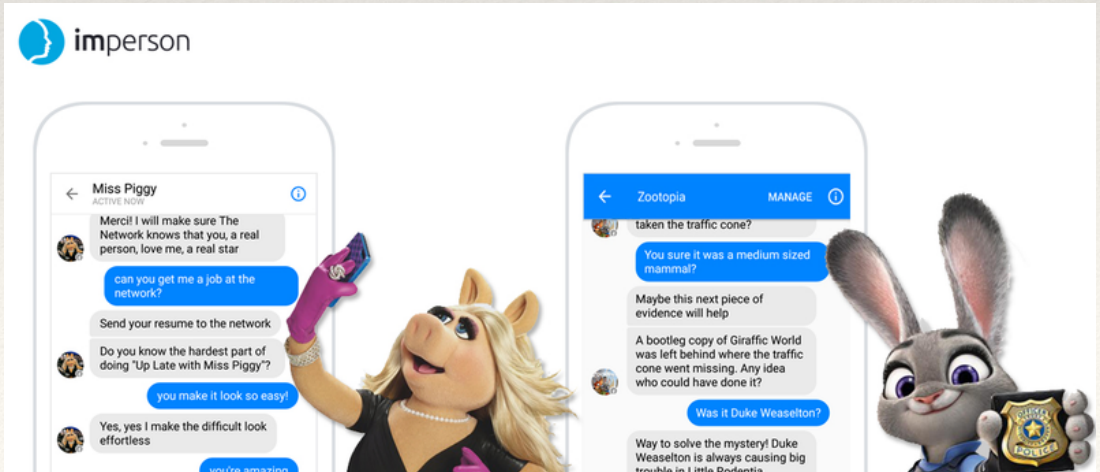
On the other hand, you have a perfectly crafted, overly trained bot that has pre-scripted fallback lines for just about every possible scenario that’s thrown at her (to further the engineering analogy, she’s been doing QA for over 30 years).”

Étienne Mérineau (Heyday)



SYSTEM LEVEL SUBJECTIVE
Personality

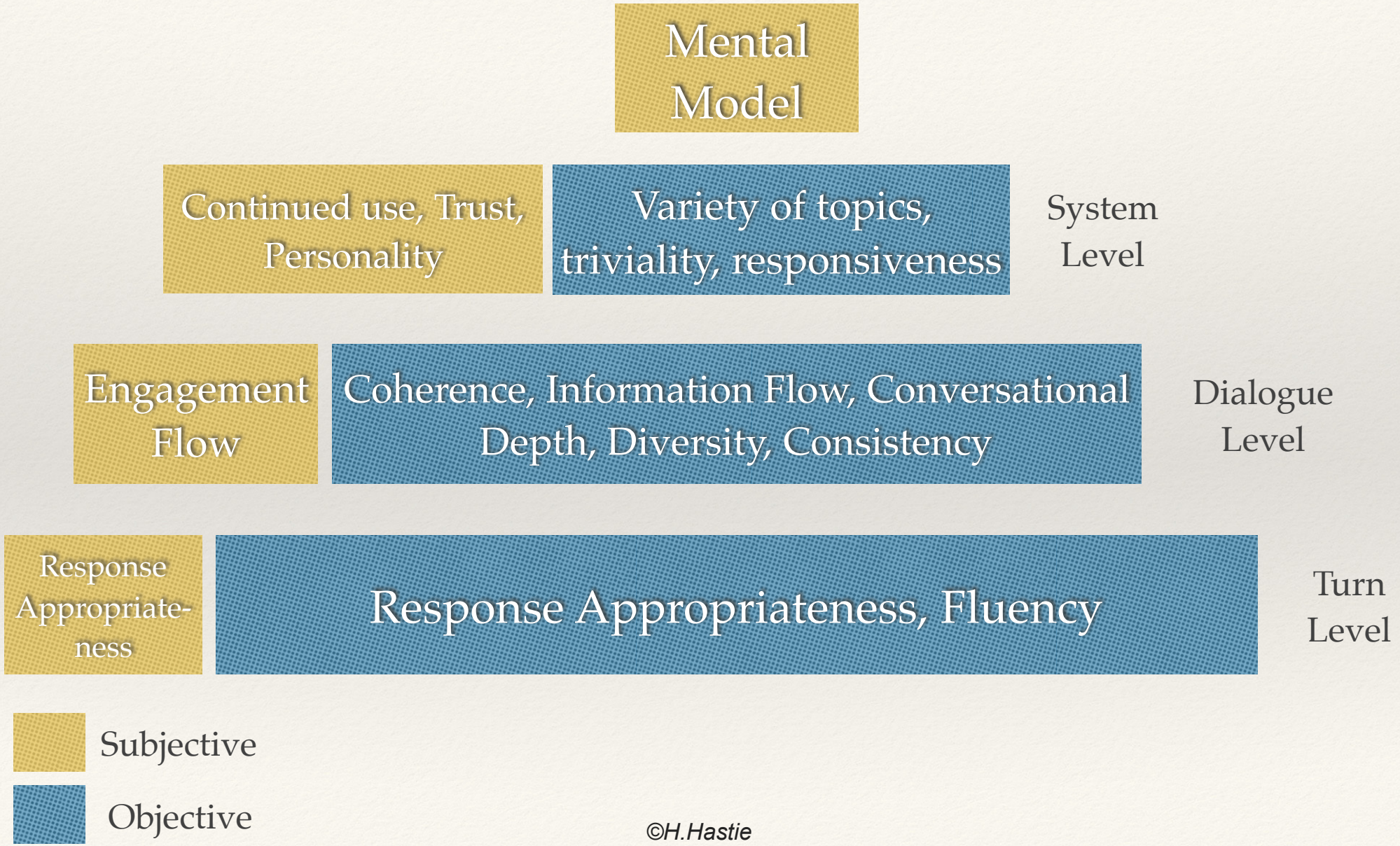
- Rule-Based chatbots can include personality traits, e.g. for better customer service
- PERSONAGE Personality Natural Language Generation (Mairesse and Walker, 2007)
- For data-driven approaches: training data can influence the system personality
  - e.g. for trainable Surface realisers (Dethlefs et al., 2013)



SYSTEM OBJECTIVE
Ability to talk on a variety of topics, triviality, speed

- System should be able to:
  - Talk on a variety of topics and change smoothly between topics,
  - should be non-trivial to enhance flow and engagement topics? How define non-trivial?
  - be highly responsive.

Evaluation Hierarchy



We are all individuals…..

Mental Models

- What the user believes about the system at hand (Nielson)
- Mental Models in cognitive theory provide one view on how humans reason either
  - functionally (i.e. understanding what the system can do)
  - or structurally (i.e. understanding how it works).

Play

Mental Models Cont.

- In HCI, designers make a user interface *communicate* the system's basic nature well enough that users form reasonably accurate (and thus useful) mental models

Mental Models Cont.

- What the user believes they know about a system strongly impacts
  - whether they use it,
  - whether they trust it,
  - how they use it.

Mental Models Cont.

Future Systems

- As systems learn new topics/skills on the fly and are constantly upgraded
- How can they subtly communicate a clear mental model to the user *on first use*
- Will they read minds and adjust interaction (i.e. Theory of Mind)

Challenges

- Loebner prize
- Alexa challenge
- WOCHAT
- SocialBot Challenge

Evaluation setting

- In the wild vs Amazon Turk
- Long term interaction
- Surviving in the real world and failing gracefully

Ethical Considerations

- The TayTweets chatbot that learned to say racist, bad things
- How can we validate sources of information we chat about?
- Socialbots are getting a bad rep: trying to get you in a social rapport and then sell you something or spread information
- Privacy of conversations
- How personal is too personal? Are chatbots contributing to the Echo chamber?

Summary

- To be a successful social chatbot, you have to be
  - engaging
  - respond appropriately and coherently but be diverse in your language
  - respond intelligently
  - draw people in and have them absorbed in the activity (flow)
  - portray a clear picture of what you can and can't do (mental model)
  - be able to discuss a wide range of topics
  - be ethical



Acknowledgements

- Dr. Verena Rieser and Amanda Cercas
- Colleagues at Interaction Lab including the Alexa team

References

- Al-Rfou, R., Pickett, M., Snaider, J., Sung, Y., Strope, B., & Kurzweil, R. (2016). Conversational Contextual Cues: The Case of Personalization and History for Response Ranking. Computation and Language.
- Belz A. and H. Hastie (2014). Towards Comparative Evaluation and Shared Tasks for NLG in Interactive Systems. In Srinivas Bangalore and Amanda Stent (eds.) Natural Language Generation in Interactive Systems. Cambridge University Press
- Brown, E. and Cairns, P. (2004). “A grounded investigation of game immersion,” in Extended Abstracts of the 2004 Conference on Human Factors in Computing Systems (Vienna, Austria, April 2004) ACM Press, pp. 1297-1300.
- Csikszentmihályi, M.; Abuhamdeh, S. & Nakamura, J. (2005), "Flow", in Elliot, A., Handbook of Competence and Motivation, New York: The Guilford Press, pp. 598–698
- Castellano, G., Paiva, A., Kappas, A., Aylett, R., Hastie, H., Barendregt, W., … Bull, S. (2013). *Towards empathic virtual and robotic tutors. Lecture Notes in Computer* (2013) Towards Empathic Virtual and Robotic Tutors. In Proceedings of AIED.
- Dethlefs, N. H.Hastie, H. Cuayáhuitl and O. Lemon (2013). Conditional Random Fields for Responsive Surface Realisation Using Global Features. In Proceedings of ACL.
- Galley, M., Brockett, C., Sordoni, A., Ji, Y., Auli, M., Quirk, C., Dolan, B. (2015). ΔBLEU: A Discriminative Metric for Generation Tasks with Intrinsically Diverse Targets. In Proceedings of ACL.
- Jennett, C., A. L. Cox, P. Cairns, S. Dhoparee, A. Epps, T. Tijs, and A. Walton. “Measuring and defining the experience of immersion in games,” in International Journal of Human-Computer Studies vol. 66, no. 9 (2008) Elsevier, pp. 641-61.
- Jeremić, Z., Jovanović, J., & Gašević, D. (2009). Evaluating an Intelligent Tutoring System for Design Patterns: the DEPTHS Experience. Educational Technology & Society, 12(2), 111–130.
- Leichtenstern, K. Andr´e,D. and Kurdyukova, E. (2010) “Managing user trust for self-adaptive ubiquitous computing systems,” in MoMM’2010
- J. Lumsden, “Triggering Trust: To What Extent Does the Question Influence the Answer When Evaluating the Perceived Importance of Trust Triggers?” in HCI, 2009.
- Li, J., Galley, M., Brockett, C., Gao, J., & Dolan, B. (2016a). A Diversity-Promoting Objective Function for Neural Conversation Models. In Proceedings of NAACL-HLT.
- Li, J., Monroe, W., Ritter, A., Galley, M., Gao, J., & Jurafsky, D. (2016b). Deep Reinforcement Learning for Dialogue Generation. In Proceedings of EMNLP.
- Li, J., Galley, M., Brockett, C., Gao, J., & Dolan, B. (2016c). A Persona-Based Neural Conversation Model. Proceedings of ACL.
- Liu, C.-W., et al. (2016). How NOT To Evaluate Your Dialogue System: An Empirical Study of Unsupervised Evaluation Metrics for Dialogue Response Generation. In Proceedings of EMNLP
- Lim, B. Y., Dey, A. K., & Avrahami, D. (2009). Why and Why Not Explanations Improve the Intelligibility of Context-Aware Intelligent Systems. In Proceedings of CHI (pp. 2119–2128).
- Litman, D. J., & Silliman, S. (2004). ITSPOKE: An Intelligent Tutoring Spoken Dialogue System. NAACL-HLT, 233–236.
- Lowe, R., Serban, I. V, Noseworthy, M., Charlin, L., & Pineau, J. (2016). On the Evaluation of Dialogue Systems with Next Utterance Classification. In Proceedings of SIGDIAL (pp. 264–269). In Proceedings of ACL.
- Möller, S., & Ward, N. G. (2008). A Framework for Model-based Evaluation of Spoken Dialog Systems. SIGDIAL, (June), 182–189. http://doi.org/10.3115/1622064.1622099
- Rigby, S., & Ryan, R. Glued to games: How video games draw us in and hold us spellbound. ABC-CLIO, Santa Barbara, CA. 2011.
- Schoenau-Fog, H. (2011). The Player Engagement Process – An Exploration of Continuation Desire in Digital Games. In Proceedings of DiGRA 2011 Conference: Think Design Play.
- Sidner, C. L., Kidd, C. D., Lee, C., & Lesh, N. (2003). Where to Look: A Study of Human-Robot Engagement. In Proceedings of ACM International Conference on Intelligent User Interfaces.
- Ritter, A., Cherry, C., & Dolan, W. B. (2011). Data-driven response generation in social media. Proceedings of EMNLP.
- Shang, L., Lu, Z., & Li, H. (2015). Neural Responding Machine for Short-Text Conversation. In Proceedings of *ACL*.
- Serban, V. Sordoni, A., Bengio, Y., Courville, A. and J. Pineau. 2016. Building end-to-end dia-logue systems using generative hierarchical neural network models. In Proceedings fo AAAI, 2016.
- Vinyals, O., & Le, Q. V. (2015). A Neural Conversational Model. In Proceedings of ICML (Vol. 37).
- Weizenbaum, J. 1966. Eliza: a computer program for the study of natural language communication between man and machine. Commun. ACM, 9:36–45, January.
- Webb, N., Benyon, D., Hansen, P. & Mival, O. (2010). Evaluating human-machine conversation for appropriateness. In Proceedings of LREC.
- Wen, T.-H. et al. (2015). Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems. In EMNLP.
- Wilks, Y. (2006). Artificial Companions as a new kind of interface to the future Internet. Oxford Internet Institute Research Report, 13.
- Xu, L., Wang, Z., Liu, Z., & Sun, M. (2016). Topic Sensitive Neural Headline Generation. Computation and Language.
- Yu, Z., Nicolich-Henkin, L., Black, A. W., & Rudnicky, A. I. (2016b). A Wizard-of-Oz Study on A Non-Task-Oriented Dialog Systems That Reacts to User Engagement. In Proceedings of SIGDIAL.
- Yu, Z., Xu, Z., Black, A. W., & Rudnicky, A. I. (2016a). Strategy and Policy Learning for Non-Task-Oriented Conversational Systems. In Proceedings of SIGDIAL .

Thank you for your attention