

ONTOLOGIES FOR ARTIFICIAL MINDS

ALESSANDRO OLTRAMARI

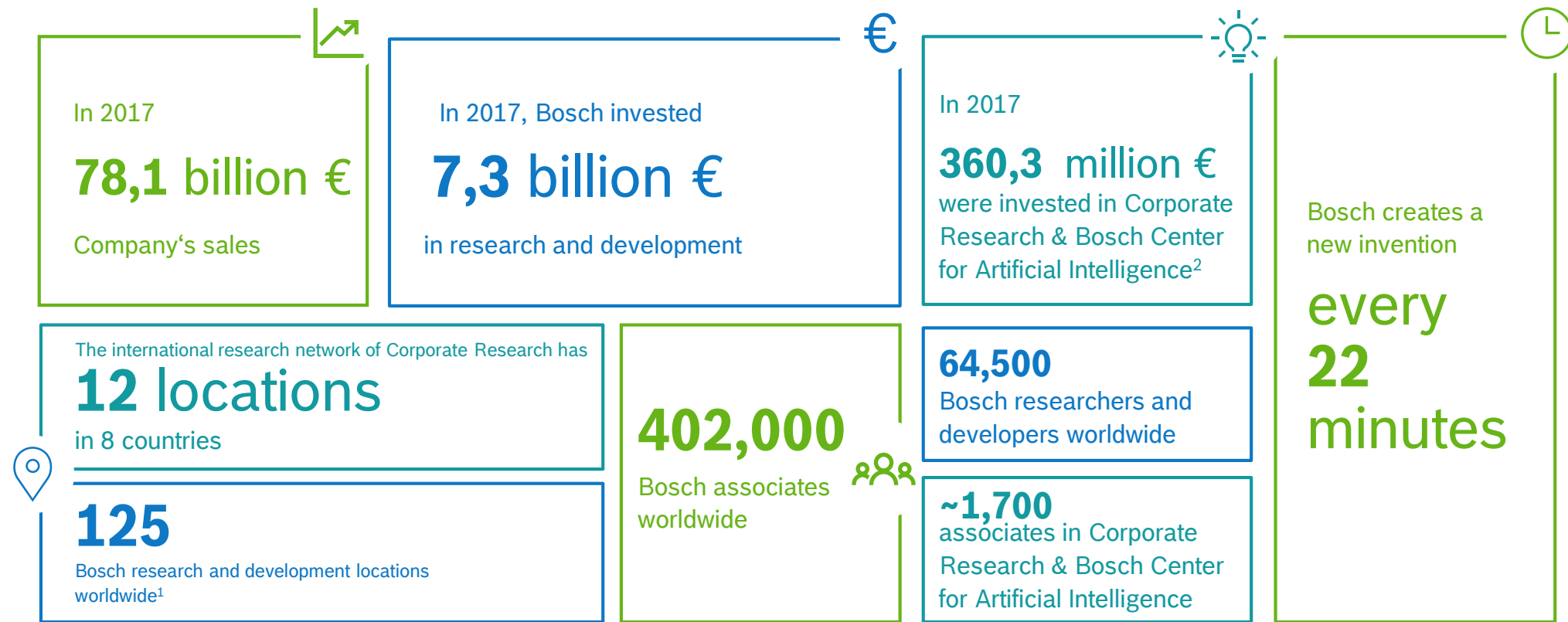
BOSCH RESEARCH AND TECHNOLOGY CENTER, PITTSBURGH (USA)

Outline

- ▶ Bosch Corporate Research (minus what I presented at JOWO)
- ▶ AI: Alchemic Intelligence?
- ▶ Knowledge-based Intelligent IoT
 - ▶ Ubiquitous Personal Assistance (UPA)
 - ▶ Neighbor-Assisted Navigation (NANNY)
 - ▶ Knowledge-based Learning Chatbot (MARK)

CORPORATE SECTOR RESEARCH AND ADVANCE ENGINEERING: CR

Figures, Facts and Locations



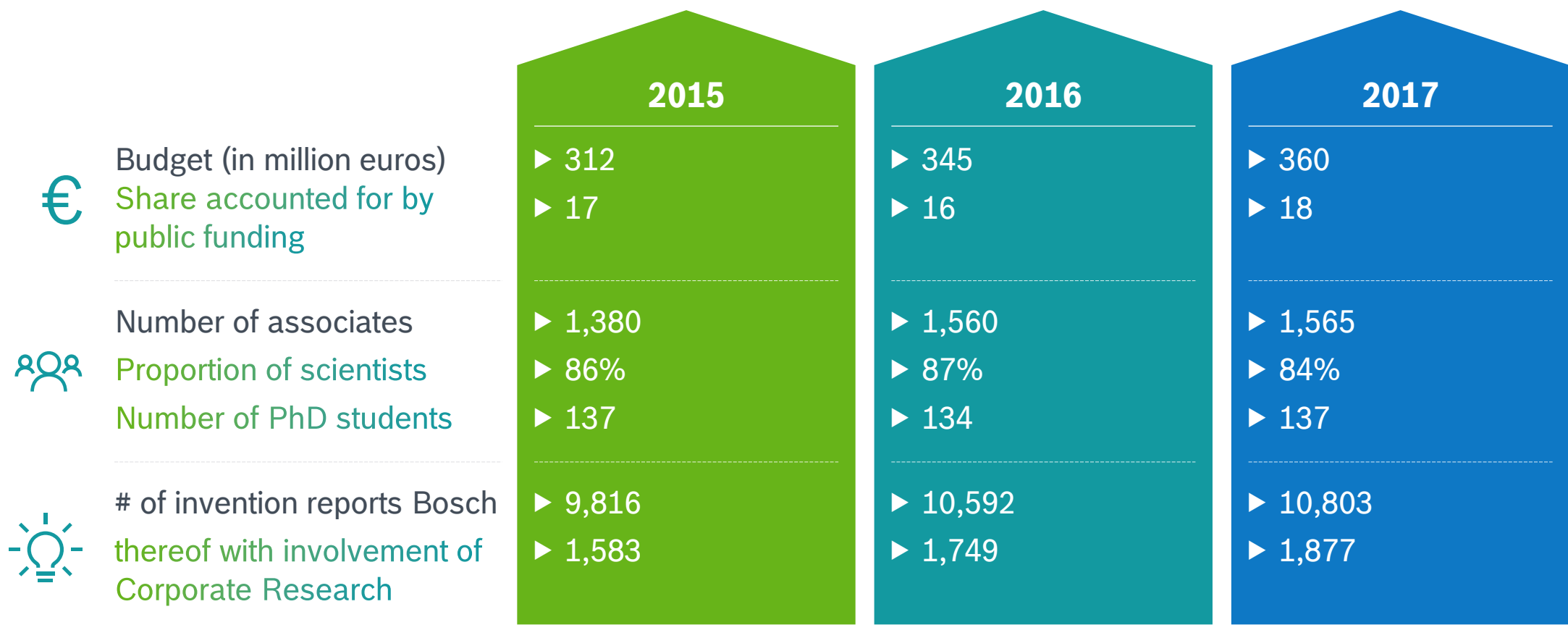
Bosch

Research and development

Corporate Research & BCAl

¹ Includes all sites with 50 or more associates, as of December 2017
² Bosch Center for Artificial Intelligence (BCAl)

Figures, Facts and Locations



Figures, Facts and Locations



America

Research and Technology Center North America

130 associates

Europe

- ▶ Corporate Research Germany
- ▶ Research and Technology Office Russia
- ▶ Research and Technology Office Tel Aviv

1.400 associates

Asia-Pacific

- ▶ Research and Technology Center India
- ▶ Research and Technology Center Asia-Pacific

110 associates

Figures, Facts and Locations



North America

Research and Technology Center

Technology scouting in America and research in the areas of

- ▶ User Technologies, Data Mining and Autonomous Technologies
- ▶ Energy Technologies and Batteries
- ▶ Software Intensive Systems
- ▶ Integrated Circuits, Wireless Technologies and Micro Electromechanical Systems (MEMS)

Organization

Balanced Organization

Competence Fields (CoFi)

Monitor and use technology trends

Continue to develop knowledge and skills

Provide Bosch with technologies, systems, and methods that are relevant for the future



Strategic Programs (SP)

Strategic alignment and bundling of activities involving related content

Strengthening of interdisciplinary cooperation

Transfer of research results to the Bosch business units

Organization

Competence Fields

Advance Engineering Systems and RTC

Future Mobility Systems	Enabling Open Context Systems	Future Systems for Industrial Technology, Consumer Goods and Building Technology
<ul style="list-style-type: none"> ▶ Powertrain and eMobility Systems ▶ Connected Mobility Systems ▶ Computer Vision ▶ Vehicle Safety & Automated Driving 	<ul style="list-style-type: none"> ▶ Model-Based Systems Engineering ▶ Dependable Connected Systems ▶ Human Machine Interaction 	<ul style="list-style-type: none"> ▶ Systems Mobile Industrial Technology ▶ Robotic Systems and Power Tools ▶ Energy Infrastructure and Building Technology
Research and Technology Center Nordamerika		
<ul style="list-style-type: none"> ▶ Circuit Design, Semiconductors and Wireless Technology 		

Applied Research and Production

Metal and Plastics Technology, Production Automation	Chemical Processes and Technology & Life Science	Future Components and Simulation Methods
<ul style="list-style-type: none"> ▶ Production Automation ▶ Joining technology, Laser material processing, electronic packaging & interconnection technology ▶ Materials- and Process Engineering Metals ▶ Plastics Engineering 	<ul style="list-style-type: none"> ▶ Analytics ▶ Functional Materials and Coating Technologies ▶ Biologically & Chemically Active Materials ▶ Microsystem and Nanotechnologies 	<ul style="list-style-type: none"> ▶ Electrodynamics and Electric Drive Technology ▶ Future Mechanical and Fluid Components ▶ Integrated Component Design

Organization

Strategic Programs

High Energy Battery
(SP-01)



Autonomous Systems &
Robotics (SP-02)



Electric Drives and
Powertrain (SP-04)



User Interaction
Technologies (SP-06)



Fuel Cell and eFuels
(SP-07)



Healthcare Solutions
(SP-09)



Urban Automated Driving
(SP-11)



Industry 4.0 - Connected
Industry (SP-13)



Computational Material
Science (SP-17)



Smart Building and
Energy (SP-18)

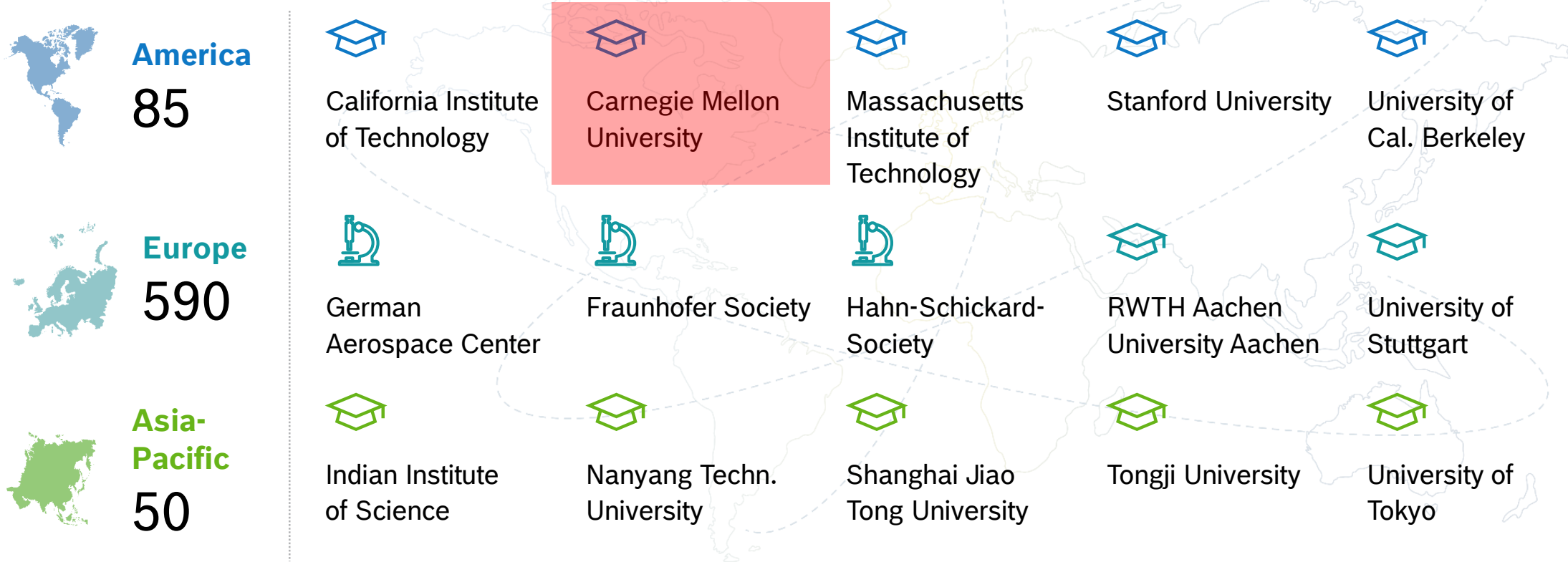


Consumer Internet of
Things (SP-19)



Scientific Environment Connected with the Best in the World

Cooperations



Strategic Focal Points Connected



Mobility

Increased convenience, efficiency and driver safety through personalized and connected mobility solutions



Smart City

Increase in energy efficiency and quality of life, improved ecological footprint through optimized use of resources

Buildings

Simplification of people's everyday lives thanks to intelligent, interconnected buildings that learn automatically



Industry

Closely interconnected industry systems increase productivity and speed during the processing of joint tasks



Connected Bosch-systems: user-oriented, intelligent and safe. Data security takes top priority.

Research and Technology Center North America

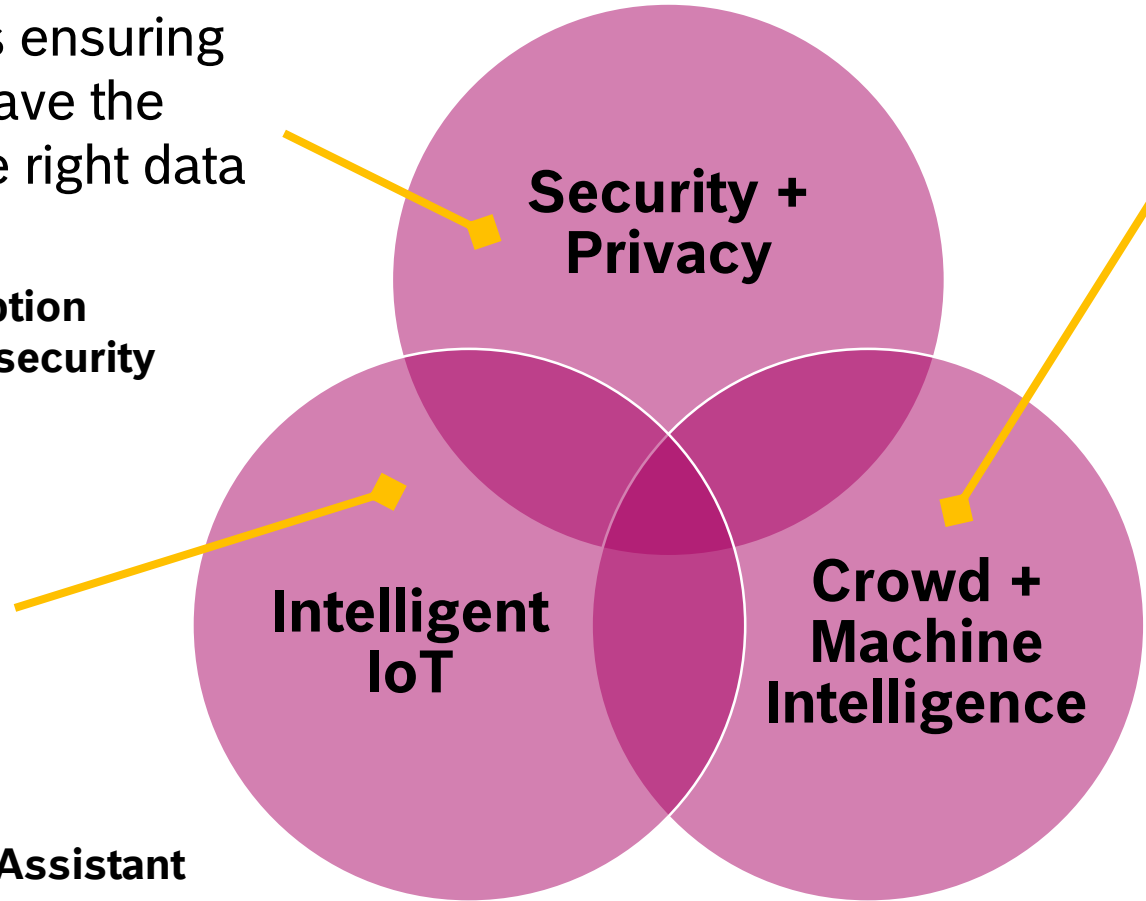
CR/RTC3-NA

Creating solutions ensuring the right people have the right access to the right data at the right time

- **Searchable Encryption**
- **AI-Powered Cybersecurity**

Applications and infrastructure that deliver innovative UX reliably and at cloud-scale

- **Smart Campus**
- **Ubiquitous Personal Assistant**



Leveraging social network technology to create productive links between communities and machines

- **Crowd AI Knowledge + Training Platform**
- **Crowd-powered Innovation**

AI ≠ ALCHEMIC INTELLIGENCE

*“We are building systems that govern healthcare and mediate our civic dialogue.
We influence elections.
I would like to live in a society whose systems are built on top of verifiable, rigorous, thorough knowledge, and not on **alchemy**”*

— Ali Rahimi, recipient of Test-of-time award @NIPS 2017

*“Forget taxonomy, **ontology**, and psychology. Who knows why people do what they do? The point is they do it, and we can track and measure it with unprecedented fidelity.*

We can stop looking for models.

We can analyze the data without hypotheses about what it might show.

We can throw the numbers into the biggest computing clusters the world has ever seen and let statistical algorithms find patterns where science cannot”

— “The Internet of Us: Knowing More and Understanding Less In the Age of Big Data” (Michael P. Lynch)



Ontologies for Artificial Minds

Alchemic Intelligence is the new Pythia



NATURE | NEWS FEATURE



Can we open the black box of AI?

Artificial intelligence is everywhere. But before scientists trust it, they first need to understand how machines learn.

Davide Castelvecchi

05 October 2016



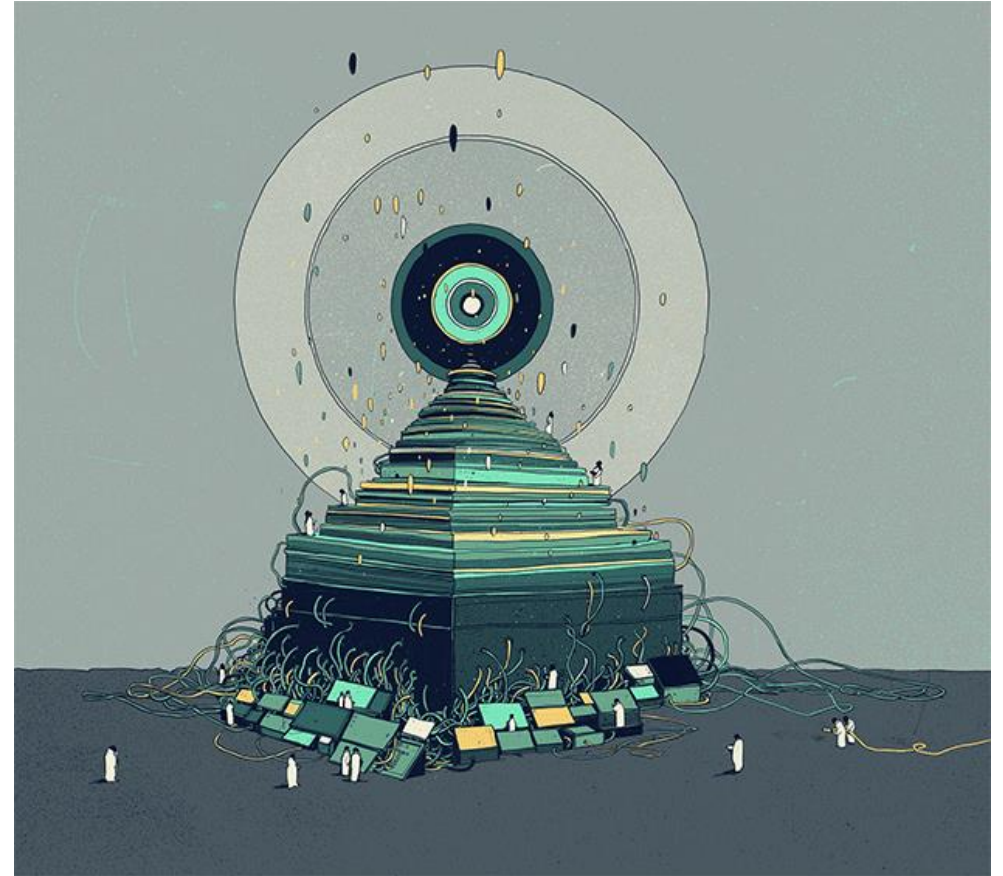
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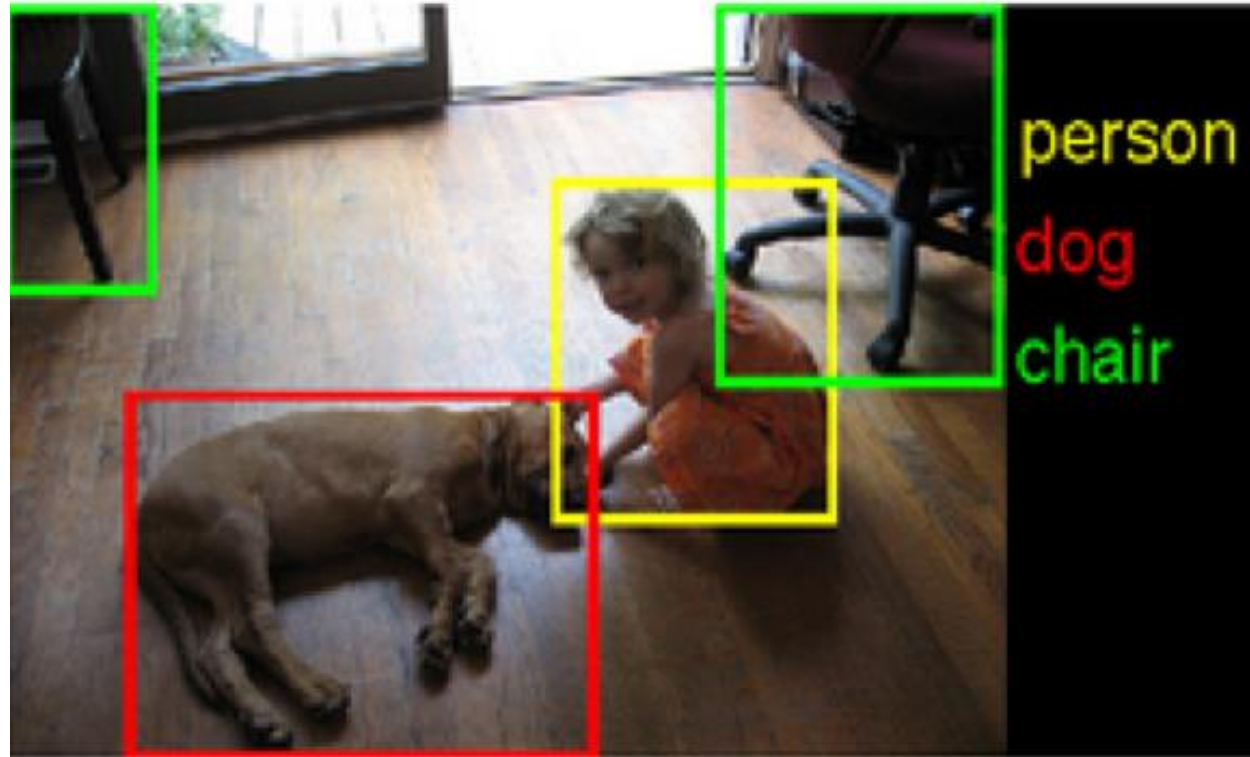


Before companies like Bosch trust commercializing AI systems, they need to provide the user with a way to access to what they learn



Ontologies for Artificial Minds

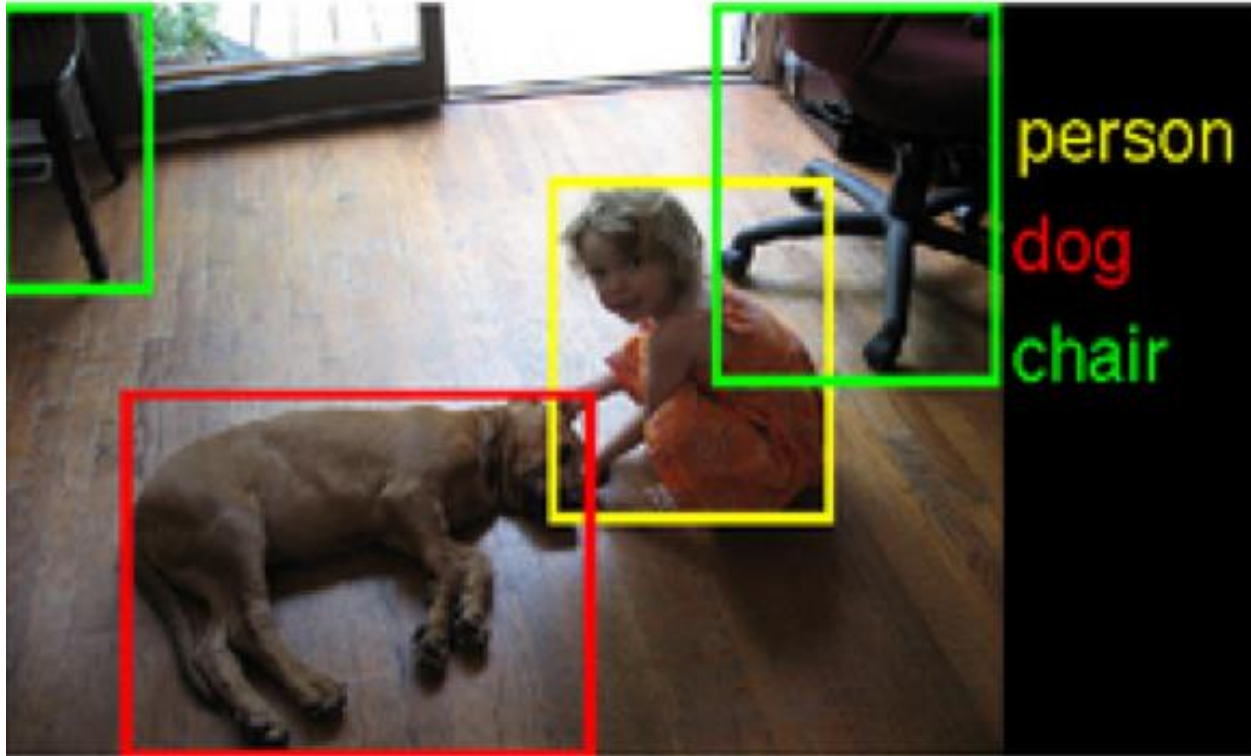
Telling dogs from chairs and persons doesn't need "explanation"



*Courtesy of
Jim Handler*

Ontologies for Artificial Minds

Saying things about the world does need explanation



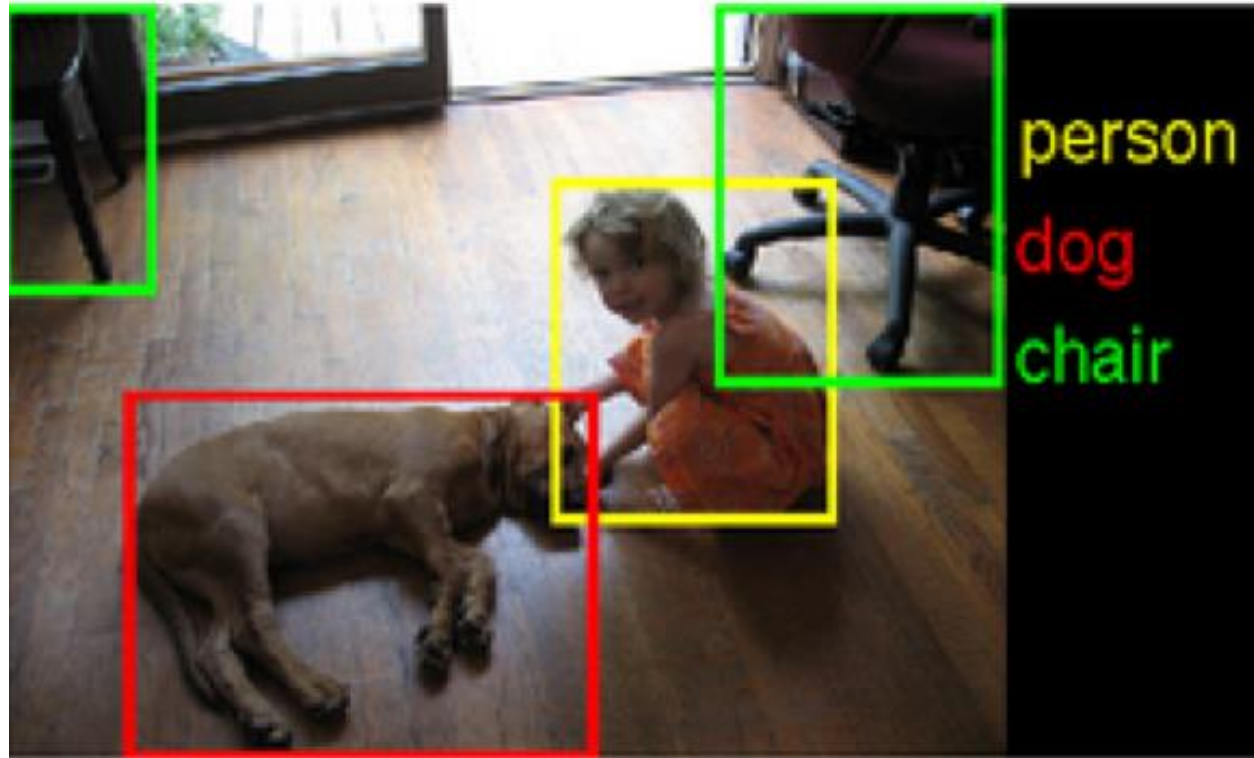
Which could you sit in?

What is most likely to bite what?

Which one is most likely to become a computer scientist someday?

Ontologies for Artificial Minds

AI-based decision support systems must become self-explainable



Which ones would you save if the house was on fire?

Would you use a robot baby-sitter without knowing which of the three possibilities it would choose?

Courtesy of
Jim Handler

Ontologies for Artificial Minds

“Intermezzo”

- ▶ Alchemy is good for AI, but science goes a long-er way
- ▶ Strong-er AI needs knowledge (not a surprise)
 - ▶ Knowledge-based IoT for Ambient Intelligence
 - Bosch projects in this context

KNOWLEDGE-BASED INTELLIGENT IoT

Knowledge-based Intelligent IoT

Intelligent Internet of Things

“To realize Ambient Intelligence, these things must understand the user’s context, including location, activities, cognitive/affective states, and social interactions, as well as the environment’s state”.

Roggen, Daniel, et al. "Opportunistic human activity and context recognition." *Computer-IEEE Computer Society- 46.EPFL-ARTICLE-182084* (2013): 36-45.

The Internet Of Things Will Be The World's Biggest Robot



Bruce Schneier, CONTRIBUTOR

I am the CTO of Resilient Systems, Inc.

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[FULL BIO](#) ▾



These "things" will have two separate parts. One part will be sensors that collect data about us and our environment. Already our smartphones know our location and, with their onboard accelerometers, track our movements. Things like our thermostats and light bulbs will know who is in the room. Internet-enabled street and highway sensors will know how many people are out and about -- and eventually who they are. Sensors will collect environmental data from all over the world.

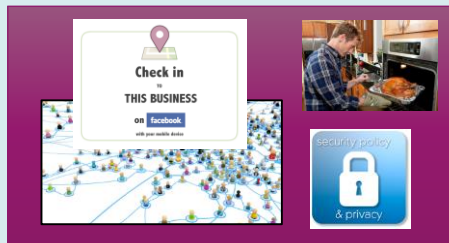
The other part will be actuators. They'll affect our environment. Our smart thermostats aren't collecting information about ambient temperature and who's in the room for nothing; they set the temperature accordingly. Phones already know our location, and send that information back to Google Maps and Waze to determine where traffic congestion is; when they're linked to driverless cars, they'll automatically route us around that congestion. Amazon already wants autonomous drones to deliver packages. The Internet of Things will increasingly perform actions for us and in our name.

CONTEXT

Sensor Network



Social and Environment



Cognition and Emotion



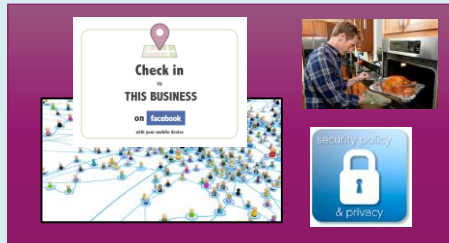
CONTEXT

KNOWLEDGE

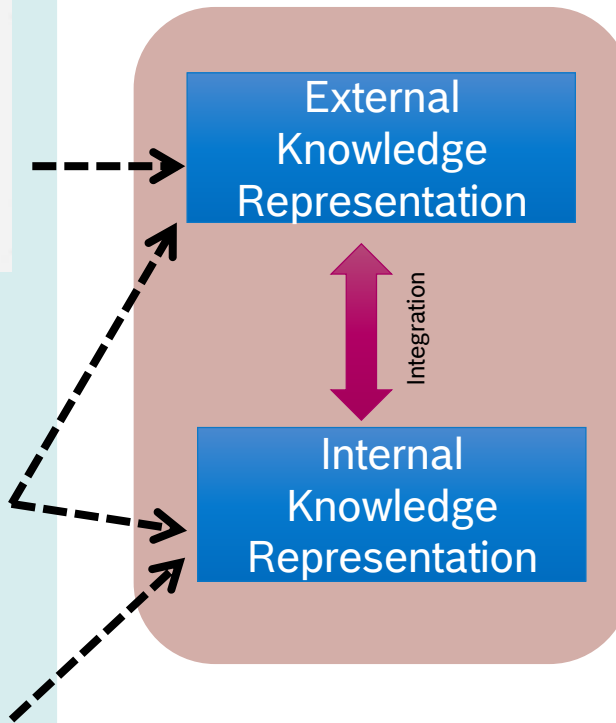
Sensor Network

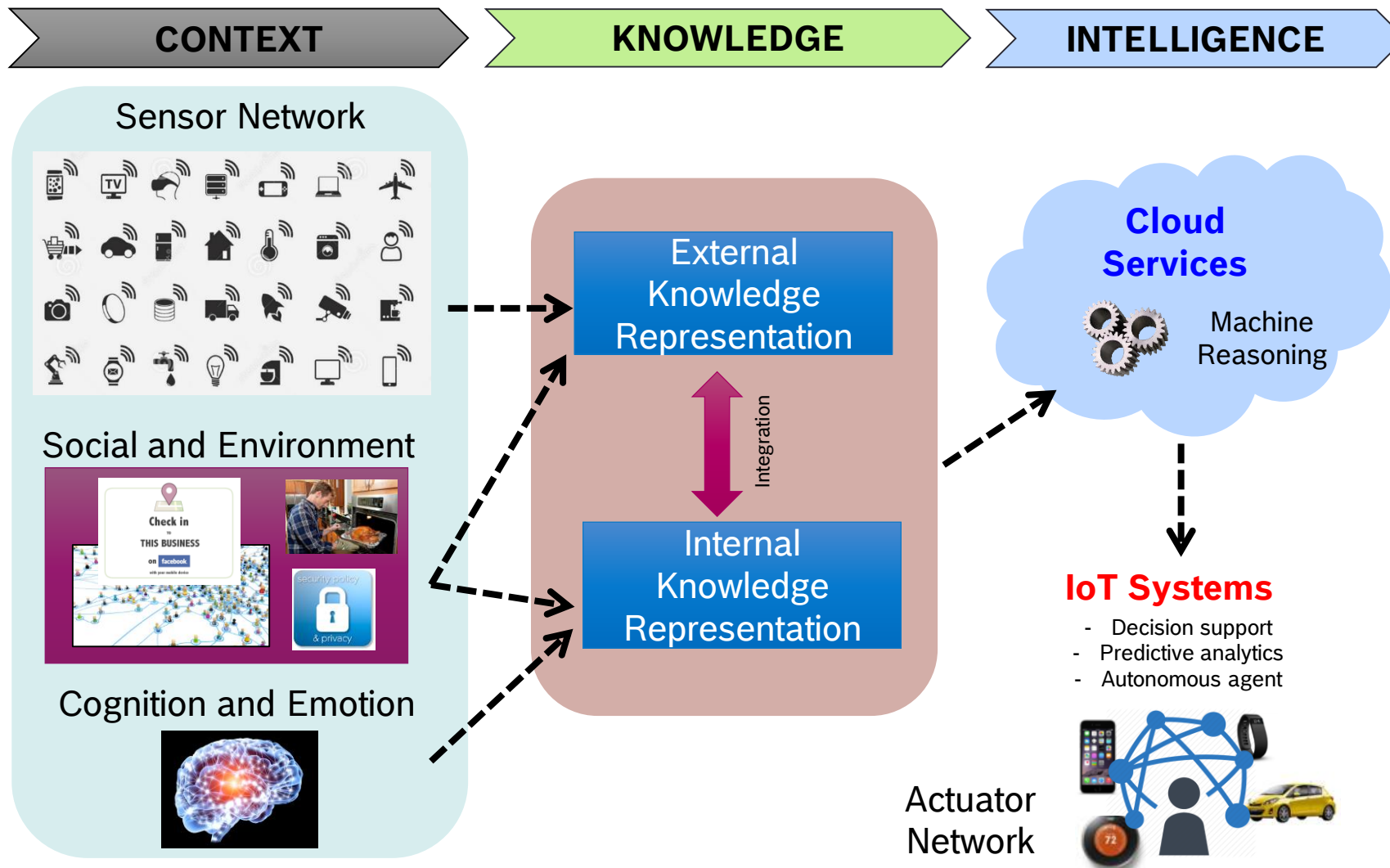


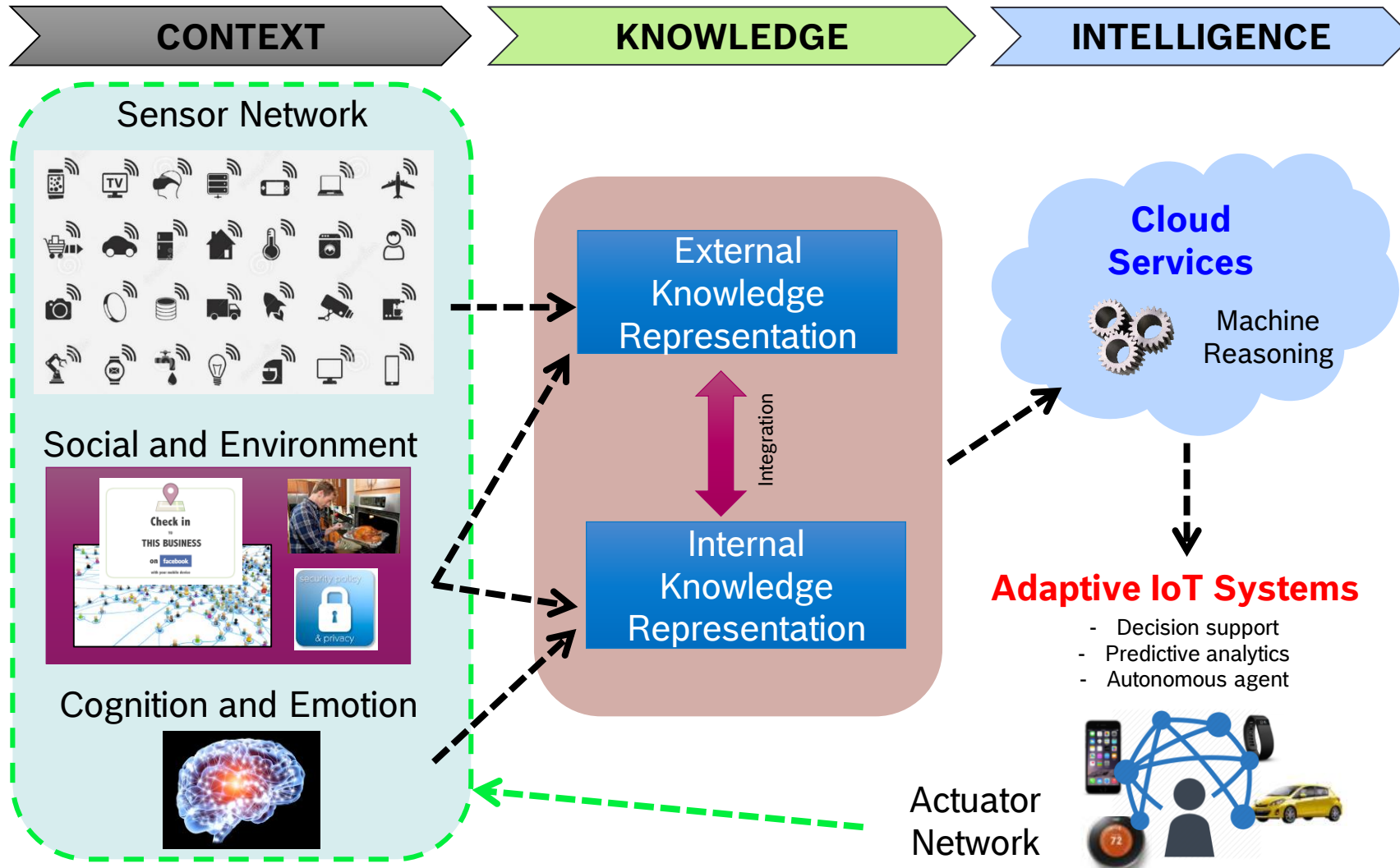
Social and Environment



Cognition and Emotion







Knowledge-based Intelligent IoT

Liaison

- ▶ The diagram is from my Bosch job talk (July 2016)
- ▶ I'm happy to assess, > 2 years later, that the vision is still valid and the projects I work fall under the umbrella of Knowledge-based Intelligent IoT
- ▶ From theory to practice, so far we have only scratched the surface of how ML/DL can be integrated with ontologies
- ▶ I work in corporate research, my job is to build prototypes that can be turned into products by BUs
 - ▶ B2C
 - Consumer IoT
 - Intelligent Assistance
 - Mobile apps
 - ▶ B2B

EMERGENCY ASSISTANT



Alessandro Oltramari, Jon Francis, Lisa Yu (CR/RTC3.1); Felix Richter (CR/AEU2)



Connected Life

Our Vision

We create the personal guardian angel – for more safety in all the adventures of life.



Knowledge-based Intelligent IoT

Modes and Usages



Location Awareness
Safe-Places & Unsafe Area

Social media
Google places
Publish user remarks



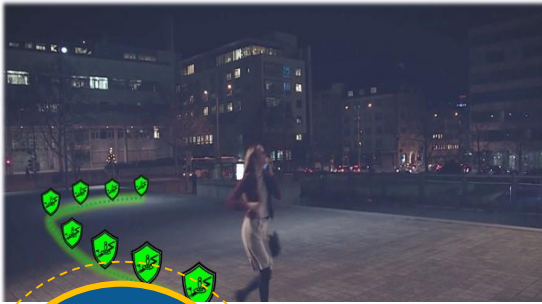
Decision Support

Consider context and risk scores to rank location & route



Accompany & Guidance

Guide and monitor user on route



Automatic Escalation

Inform call-center agent in case of alarm

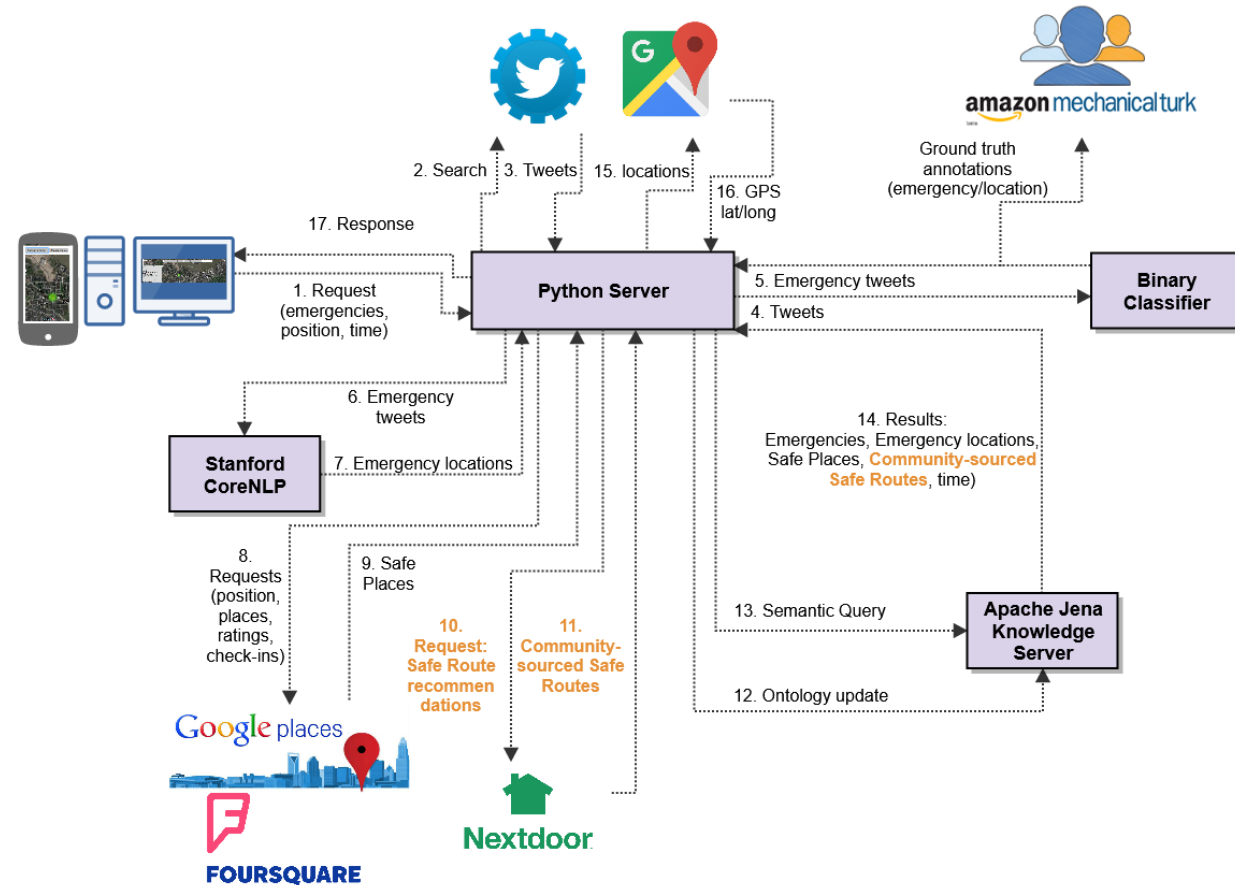


Route Deviation



Knowledge-based Intelligent IoT Architecture and Run-time Processes

- ▶ Request to Twitter Search API
- ▶ Response: 100 tweets in JSON
- ▶ Classification of tweets: emergency (Y/N)
- ▶ Emergency(Y) tweets sent to NLP module
- ▶ Emergency locations are extracted (e.g., “PNC Park”)
- ▶ Safe Places in the user surroundings are retrieved
 - ▶ *Safe routes also available at community level*
- ▶ Ontology updated with extracted information
- ▶ Query → *location/time/type of emergency + safe places*
- ▶ Ontology Server returns results in JSON
- ▶ Ontology results are transformed in GPS coordinates and visualized in the a heatmap (to end user or call center operator)



Knowledge-based Intelligent IoT Evaluation

Tweet Classification

CLASS	P	R	F1-SCORE
Threat-related tweets	0.93700	0.9914	0.96347
Non threat-related tweets	0.81115	0.3545	0.49341
Avg. / total	0.92521	0.9318	0.91946
CONFUSION MATRIX			
1371 (TP)	1085 (FN)		
42 (FP)	172 (TN)		

Location Recognition

P	R	F1-SCORE	Jaccard Score
0.97027	0.55822	0.708710	0.3
CONFUSION MATRIX			
7094 (TP)		61(FN)	
477 (FP)		262 (TN)	

We conducted a crowdsourced study to obtain ground truth. When location mentions are structurally simple (e.g., “Stamford Bridge”, “Eltham”, “Springfield, VA”), NER is highly accurate. Heterogeneity in location mentions (e.g., abbreviations, style of tweets, etc.) represents a challenge for the system, but (unsurprisingly) not for humans.

Knowledge-based Intelligent IoT

Federating UPA Knowledge Silos with a Modular Infrastructure

SSN: W3C Semantic Sensor Network Ontology (open standard for IoT)

UPA Core: TBD (common layer on top of UPA domain ontologies)

EXAMPLE

CL: PoisonousFumesInhalation

SSN: isTriggeredBy

DIY: Painting

SSN: Uses

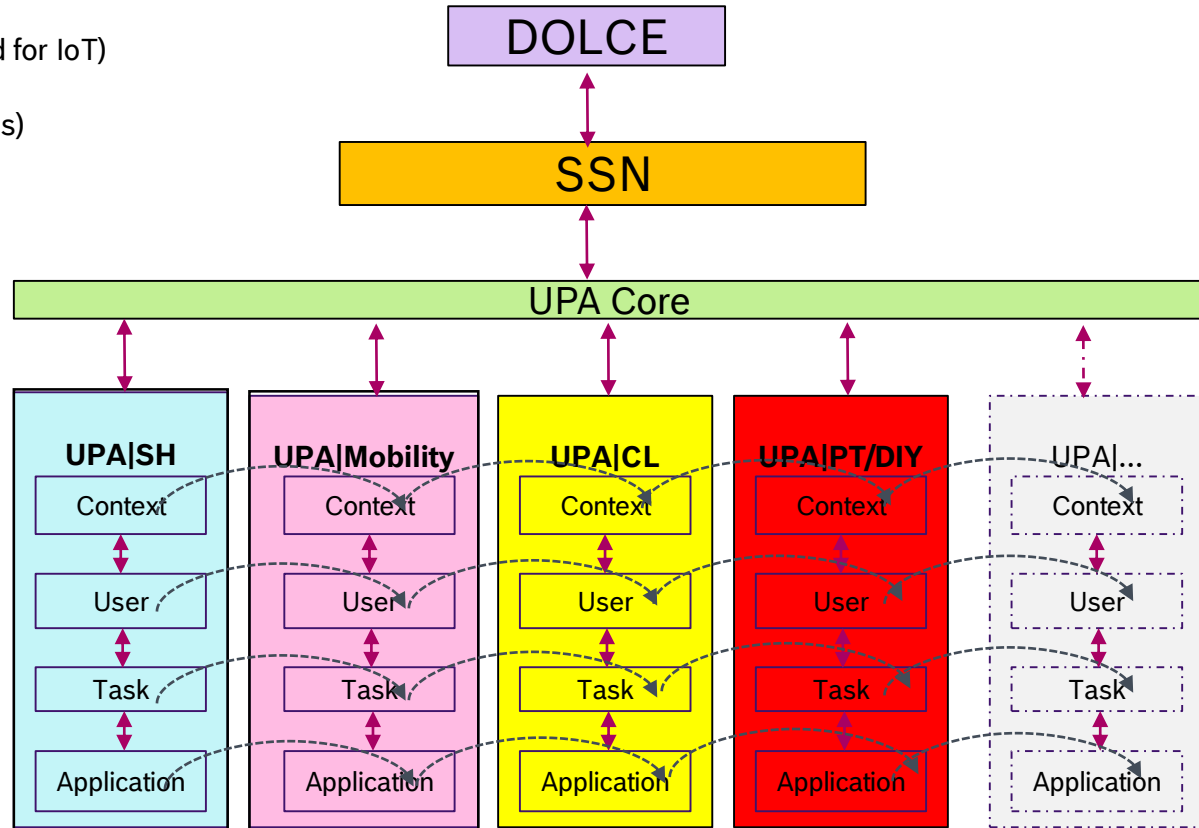
PT: PFS2000PaintSpraySystem

SSN: hasParticipant

CL: Caller

SSN: hasLocation

SH: Garage



UPA-CL Highlights

2 Prototypes

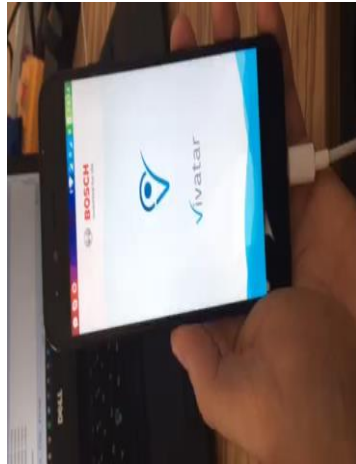
Technical Emergency Assistant (T-EA)

Based on user's location, the T-EA displays a heatmap of emergencies inferred from Twitter (v2.0 blow includes "safe locations" retrieved from Google Places ratings)



Decision Support Emergency Assistant (DS-EA)

Recommendation engine for safe places based on distance between user and place, Google Place ratings, type)



3+1 FEBER reports

1. Analysis of academic and commercial solution landscape with respect to T-EA/DS-EA functionality (CR-AEU-006)
2. Ubiquitous Emergency Assistance: Augmenting Location Awareness in Safety-related Situations(CR/SP-19-888-1032)
3. Generating private dialogue using crowdsourcing (CR/SP-19-888-1031)
4. *Ubiquitous Emergency Assistance: Safe places ranking* (Q4-2018)

2 provisional patent applications

Guide to Public Safe Location

(IR-No: 2017/5848)

Process for navigating to safe place using mobile devices, by leveraging Google Maps and machine learning algorithms

Crowd 911: Generating Sensitive Dialogue Through Lightweight Simulation"

(IR-No: 2017/8927)

Text-based interface where crowdworkers - playing the role of 911 callers - and free lance dispatchers simulate emergency conversations

Ontologies for Artificial Minds

Self-explainable Chatbot for Emergency Assistance

- Front-end: chatbot can be used as vehicle of explanation

Call Center Agent: *“Emergency Assistant why are you recommending to call the ambulance? The user is only reporting fatigue and headache”*

Emergency Assistant: *“I found that the user was hospitalized for heart attack 2.5 years ago. Judging by the general trend for this kind of disease, in people over 40, we shouldn’t overlook the symptom. Better safe than sorry!”*

Call Center Agent: *“Gotcha, thanks for spotting this”*

- Back-end

- Integrating off-the-shelf conversational capabilities (chatbots) with knowledge representation and reasoning
- Pairing Knowledge Graphs structures with DL patterns
- Reinforcement Learning can leverage user’s feedbacks to make transduction more robust

MARK: KNOWLEDGE-BASED LEARNING CHATBOT



Alessandro Oltramari, Jon Francis (CR/RTC3.1)

Monireh Ebrahimi (Wright State University), Sarah Masud Preum (University of Virginia)

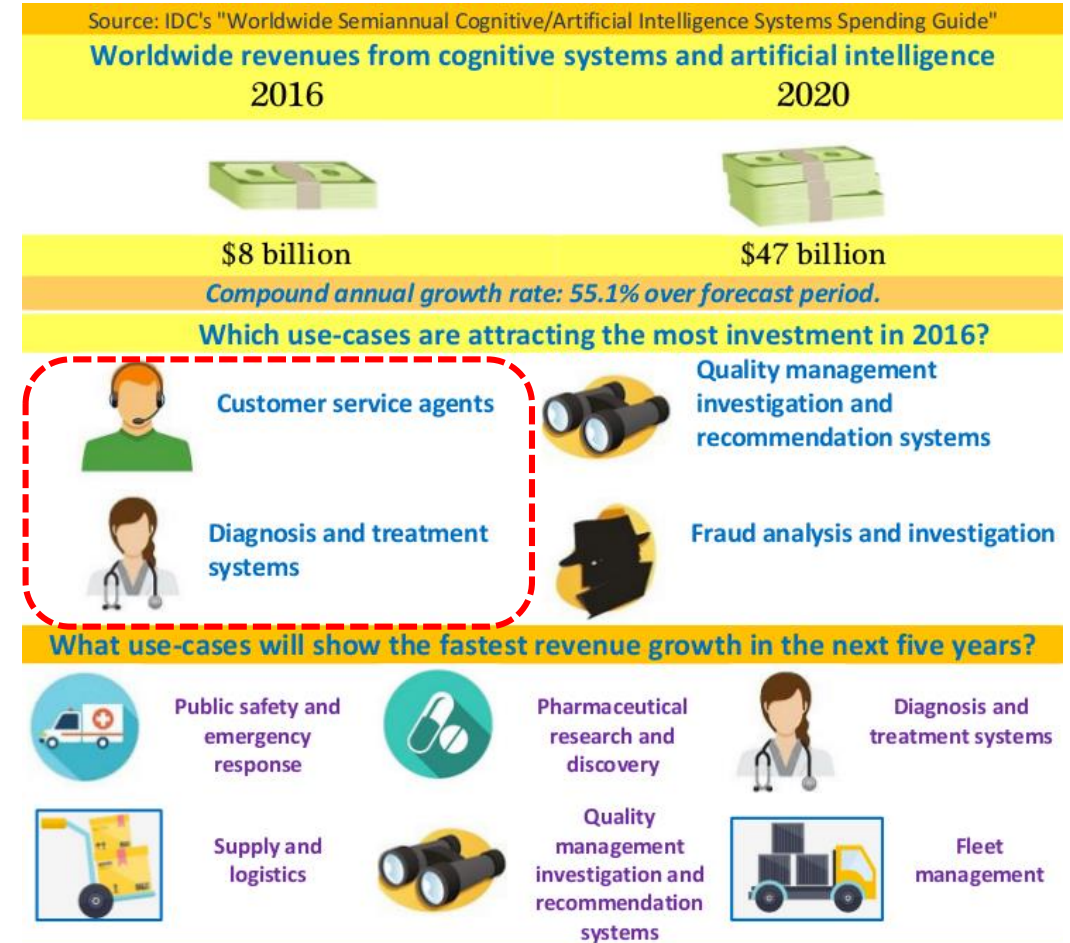
Knowledge-based Intelligent IoT Chatbots: Hype vs. Reality

- ▶ Millions of chatbots populate the virtual world...
 - ▶ Riddled with bugs
 - ▶ Limited conversational capabilities
 - ▶ Work with limited knowledge (book flights)
- ▶ Challenges of building robust chatbots:
 - ▶ Consistent interpretation of a user's input
 - ▶ Generation of context-relevant output
 - ▶ Diverse and representative data
 - ▶ Dealing with sizeable heterogeneous knowledge

<https://www.clickz.com/7-reasons-not-to-believe-the-chatbot-hype/111700/>
<https://venturebeat.com/2017/01/30/5-reasons-not-to-believe-the-chatbot-hype/>

Knowledge-based Intelligent IoT AI for Customer Assistance

- ▶ Operators handle calls as they deem appropriate according to training, best practices, scripts
- ▶ **Problems: Scalability/Cost/User-Satisfaction**
 - ▶ A conventional model of call center that exclusively relies on humans suffers from **scalability problems** with high-volume of traffic, is expensive, and depends on individual skills/expertise (a factor that may hinder consistently-high standard in service quality)
- ▶ **Solution: AI-based decision support systems**
 - ▶ Reasoning, Learning, Language Understanding,...



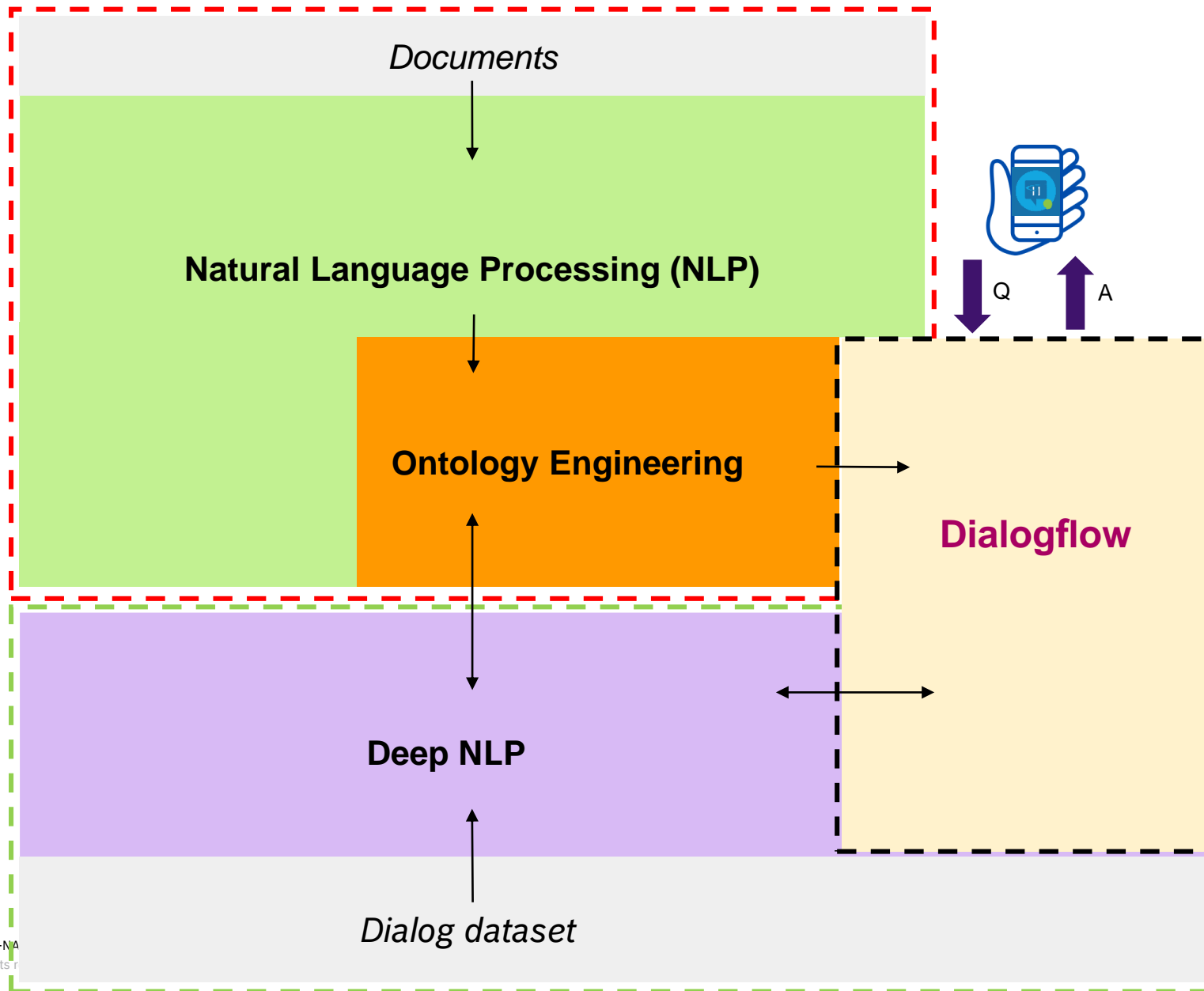
Knowledge-based Intelligent IoT

Overview

- ▶ **Problem:** in the US health market, the *knowledge divide* between Offer and Demand breaks communication among customer, care provider, insurance.
- ▶ **Solution:** intelligent chatbot for effective and scalable customer support in healthcare services
- ▶ **Business Validation:** domain-agnostic knowledge-based deep learning system that aggregates heterogeneous data and conveys information through natural language interaction.
- ▶ **Progress**
 - ▶ Chatbot under construction using IBM Watson Q/A dataset (17K pairs collected from Insurance Library website) + 20 Insurance Documents from [Office of Personal Management](#) (open data)

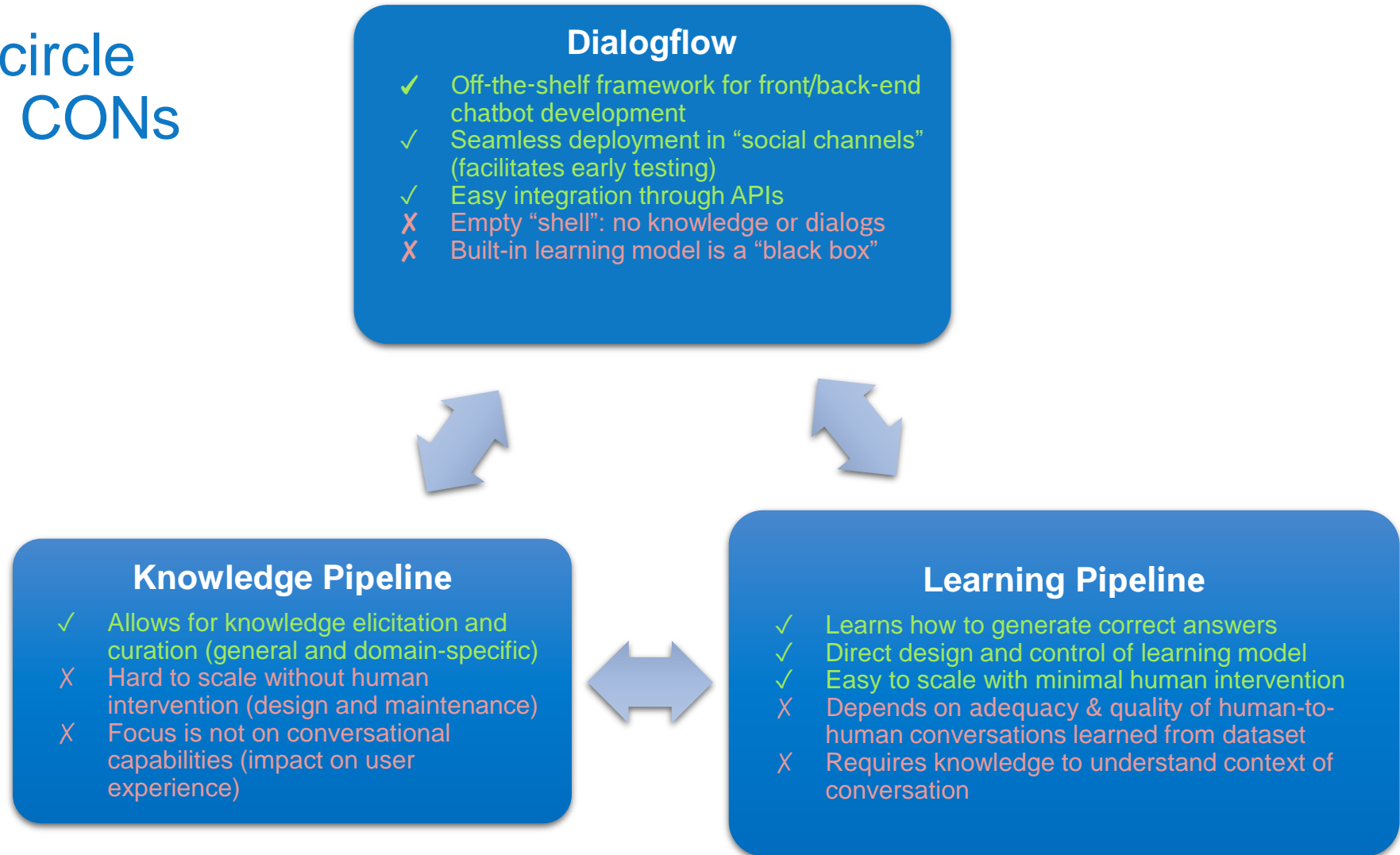
**Knowledge
pipeline
(KEPLEHR)**

**Learning
pipeline
(DEEPhR)**



MARK

The virtuous circle of PROS and CONS



MARK PRE-STUDY

MARK MVP1's Hybrid Architecture: maximizing the PROs

MARK MVP1



- ✓ Off-the-shelf framework for front/back-end chatbot development
- ✓ Seamless deployment in “social channels” (facilitates early testing)
 - ✓ Easy integration through APIs
- ✓ Allows for knowledge curation (general and domain-specific)
 - ✓ Learns how to generate correct answers
 - ✓ Direct design and control of learning model
- ✓ Easy to scale with minimal human intervention

 **WARNING**

PREREQUISITE:

**Dataset of call
transcripts + plan
documents**

Knowledge-based Intelligent IoT

Health Insurance Ontology: Existing resources

*Low coverage of
HI domain*

► Schema.org:

- Health insurance specific: health insurance plan, health plan network, health plan formulary, health plan cost sharing specification, insurance agency
- Medical entities: medical therapy, patient, medical procedure, drug, medical clinic, diagnostic procedure

► Related literature:

► The ontology of medically related social entities [Hicks et al. 2016]

- Demographic data
 - Race, ethnicity
 - Smoking status, marital status
- Health care facilities
 - Hospital, urgent care, nursing home

*Recommendation
for knowledge
representation*

► A cloud based health insurance plan recommendation system: A user centered approach [Abbas et al. 2014]

- 11 types of plan coverage
 - inpatient, outpatient, pediatric, maternity, emergency care, prescription medication, dental, etc.

*Taxonomy rather than
formal ontology*

Knowledge-based Intelligent IoT

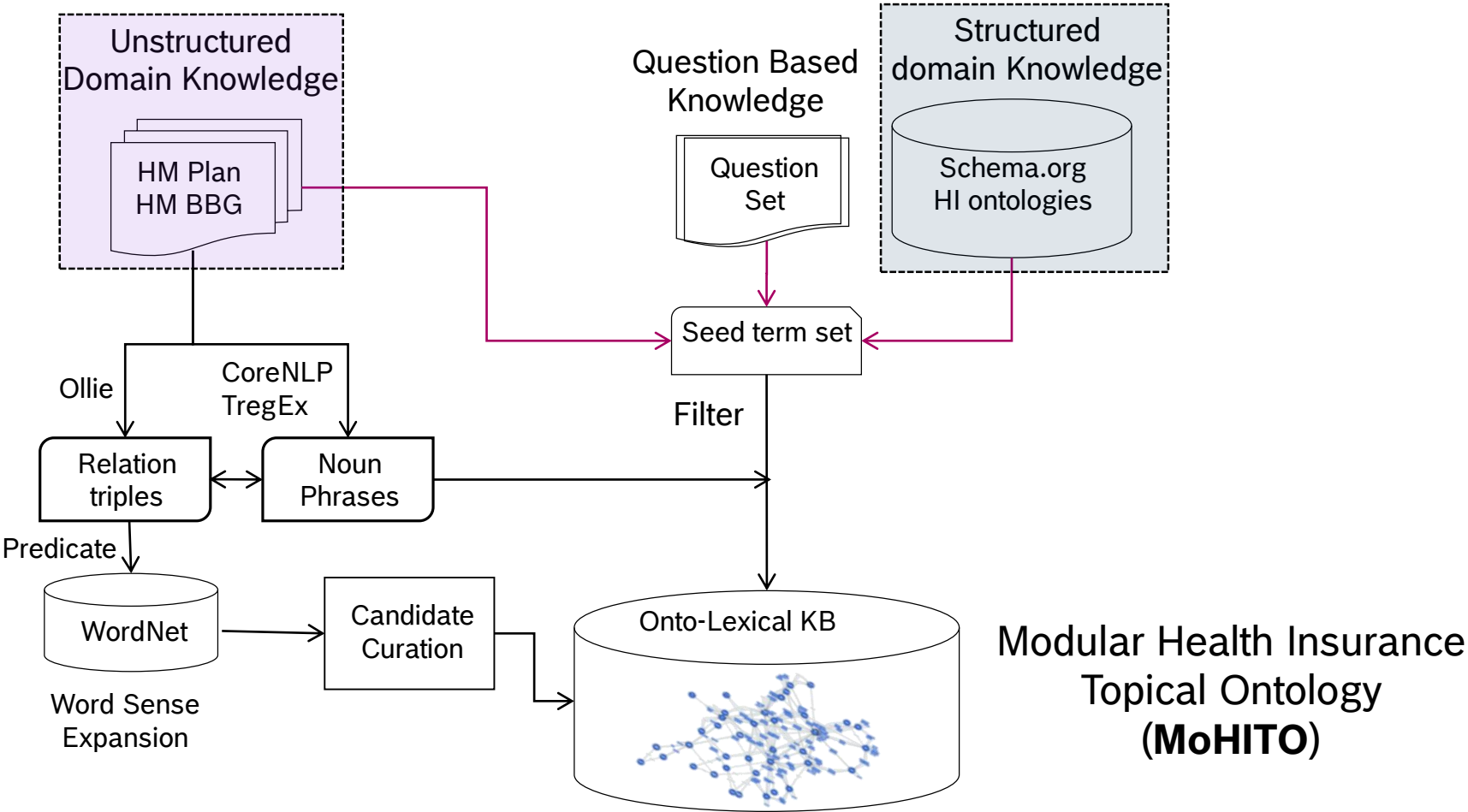
Entity:

Employee benefit plan,
Organ transplant procedure,
Outpatient procedure

Relation:

Part of the local blue shield ppo network will be covered at the enhanced value level of benefits.

Arg1: Part of the local blue shield ppo network
Predicate: cover
Arg2: the enhanced value level of benefits



Knowledge-based Intelligent IoT

Our contribution using KEPHLER

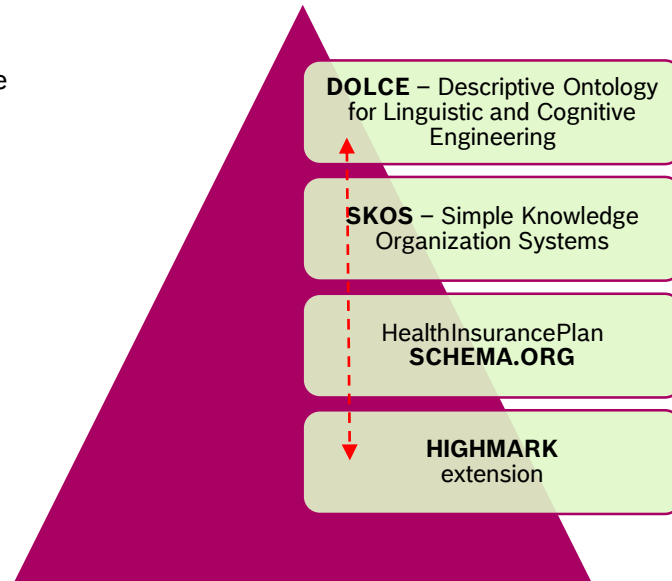
- ▶ Layered knowledge infrastructure for semantic representation of health insurance documents
- ▶ Guide what deep networks should learn from conversation context/history

Built in 2004, widely used in many applications, provides reference axioms for reasoning in different domains

Designed in 2009, anchors lexical contents to Semantic Web specifications

Founded by Google, Microsoft, Yahoo and Yandex in 2011, Schema.org vocabularies are developed by an open community process, using the public-schemaorg@w3.org mailing list and through GitHub.

Extension of Schema.org classes and properties related to Health Insurance Plan, represents knowledge required to answer relevant questions

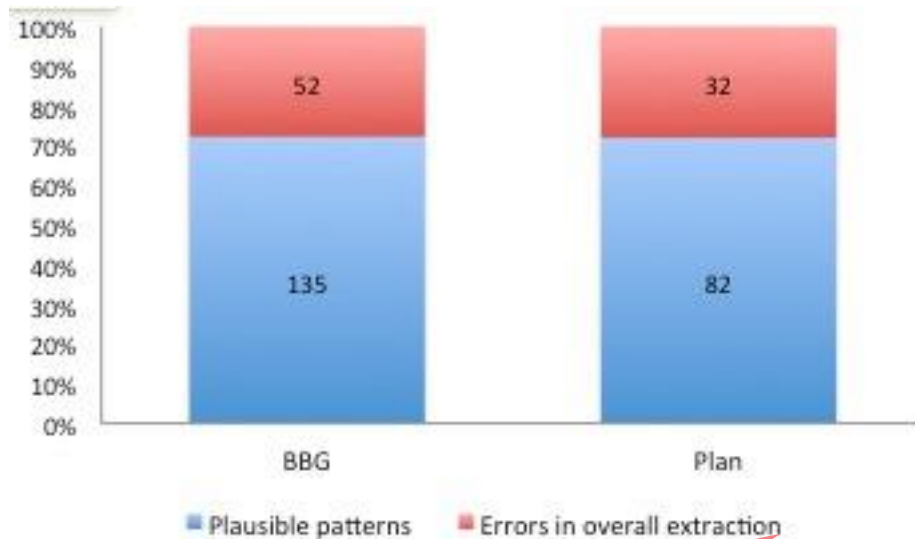


- *Top Level Ontology*
- *W3C standard model for controlled vocabularies, taxonomies, thesauri*
- *Core set of schemas for structured data mark up*
- *Domain-specific concepts linked to Q/A space*

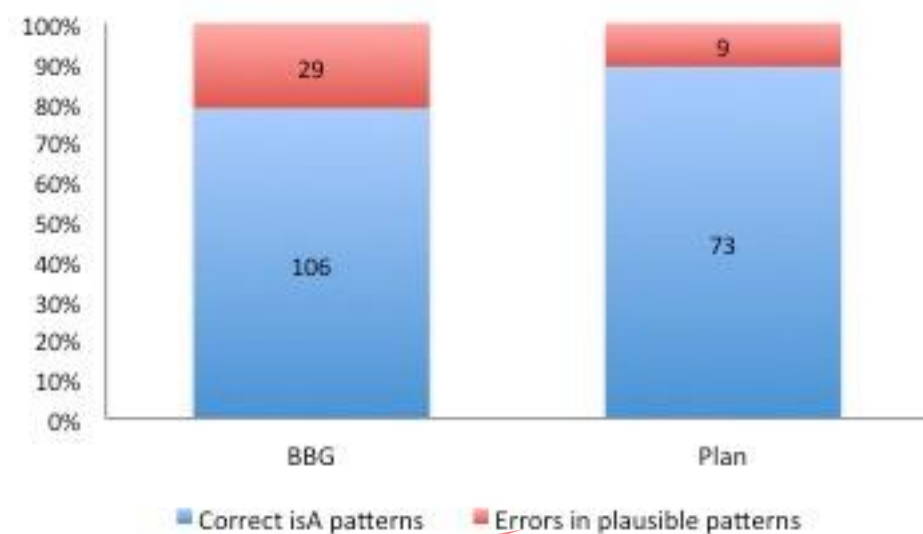
Knowledge-based Intelligent IoT

Extracting taxonomic relations using extended Hearst Patterns

- ▶ Automatically extract potential taxonomic/ isA relations from unstructured text using predefined linguistic patterns
- ▶ Count of original Hearst patterns: 5
 - ▶ Extended over time through public contribution: 48 additional patterns



Error: mis-classify non-relation as a relation

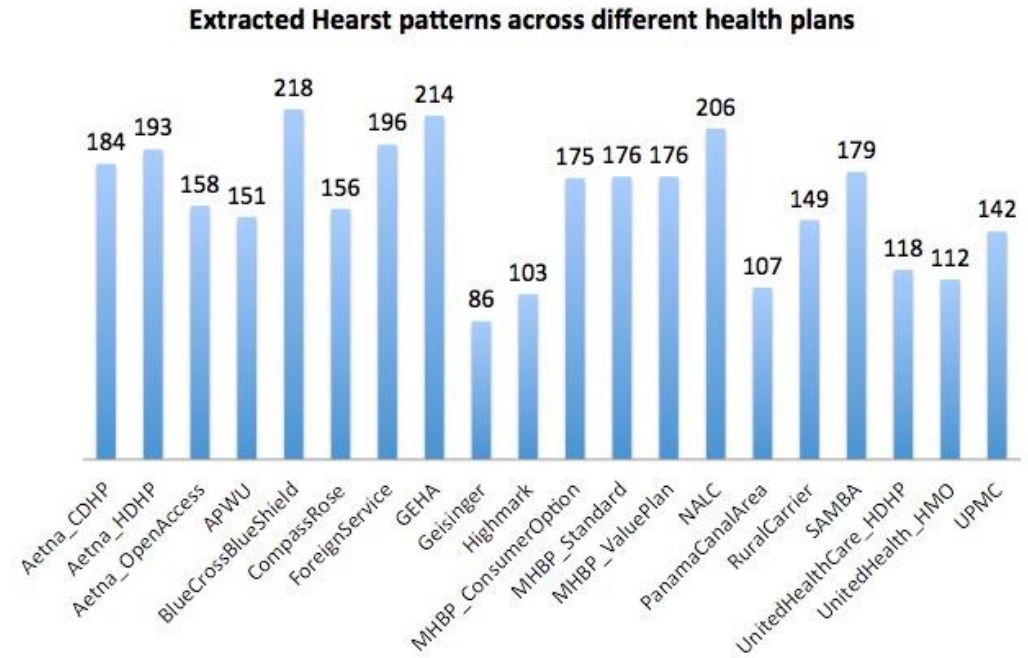


Error: mis-classify isA relation

Knowledge-based Intelligent IoT

Cross Document Analysis of Health Insurance Plans

- ▶ KEPLER for 20 health insurance documents
 - ▶ Hearst Patterns
 - ▶ Contain duplicates
 - ▶ Contain non-taxonomic relations
 - ▶ Future work:
 - Develop classification model to identify correct taxonomic relations



Knowledge-based Intelligent IoT

From domain specific documents to formal ontology: challenges

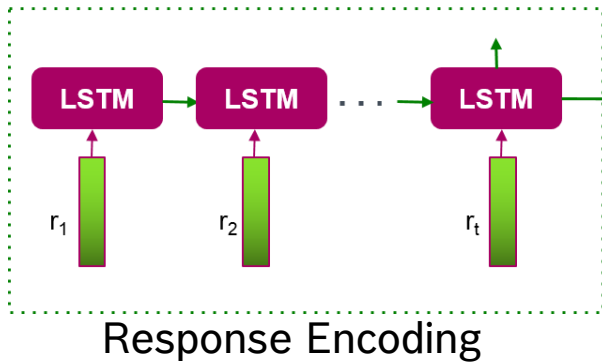
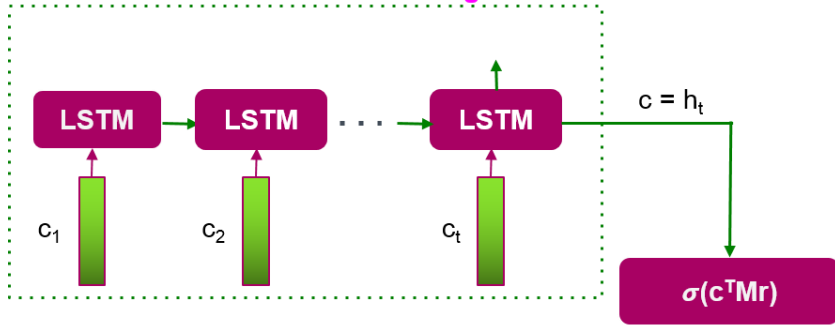
- ▶ Hundreds of potential relevant entities and relations
- ▶ Remove noise from the extracted information
- ▶ Extract (more) relevant information
 - ▶ Coreference resolution, entity linking
- ▶ Normalize entities and relation
 - ▶ Semantic
 - Medical preventive care \leftrightarrow preventive medical care \leftrightarrow preventive care
 - Pre-authorization \leftrightarrow plan approval
 - ▶ Syntactic:
 - X-ray \leftrightarrow x-rays
 - ▶ X covers Y \leftrightarrow Y is covered by X
- ▶ Align them with ontological structure
 - ▶ Arg1 of cover is likely to be a plan
 - ▶ Arg2 of cover is likely to be a covered service



Knowledge-based Intelligent IoT

Deep learning pipeline (DEEPHR)... in a nutshell

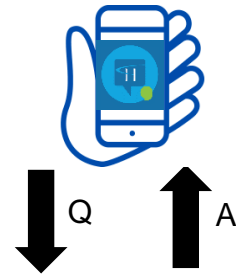
Context/Question Encoding



Onto-lexical patterns (from KB),
user profile information,
mobile app. context

Training
Data*

Domain specific
semantic annotations



Dialogflow

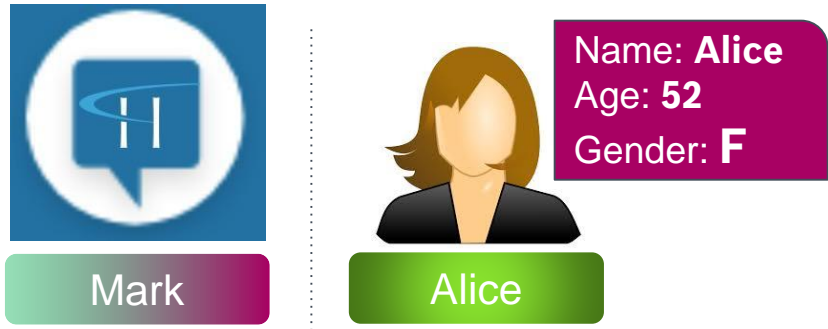
Intents, Entities, Synonyms,
Parameters, Parameter
values, training phrases,
answers

Deep Learning Model

Dialogue flow intent
Concept extraction model
Word embedding model
Question clustering

Knowledge-based Intelligent IoT

Deep Learning Pipeline for Highmark: a simple example



Mark

Alice

Name: Alice
Age: 52
Gender: F

Adults: Ages 19+ Male Female

General Health Care

Procedure	Frequency
Routine Checkup* (This exam is not the work- or school-related physical)	• Ages 19 to 49: Every 1 to 2 years • Ages 50 and older: Once a year
Pelvic, Breast Exam	Once a year

Alice: Hi Mark, I am wondering which type of general health service I can get from Highmark?

Mark: Hi {Alice}, you can use our routine checkup once a year plus {pelvic and breast exams}.

...

...

- **Name/Gender** → Profile
- **Procedure** → BBG/Plan
- **Coverage** → BBG/Plan
- **Sentence structure** → dialog examples

Knowledge-based Intelligent IoT

Retrieval-based Model: Preliminary Results

Model	Recall@1	Recall@2	Recall@5	Recall@10
Dual LSTM Encoder	0.45	0.64	0.92	1.00
TF-IDF	0.80	0.89	0.96	1.00
Random	0.09	0.19	0.50	1.00

NEIGHBOR-ASSISTED NAVIGATION (NANNY)

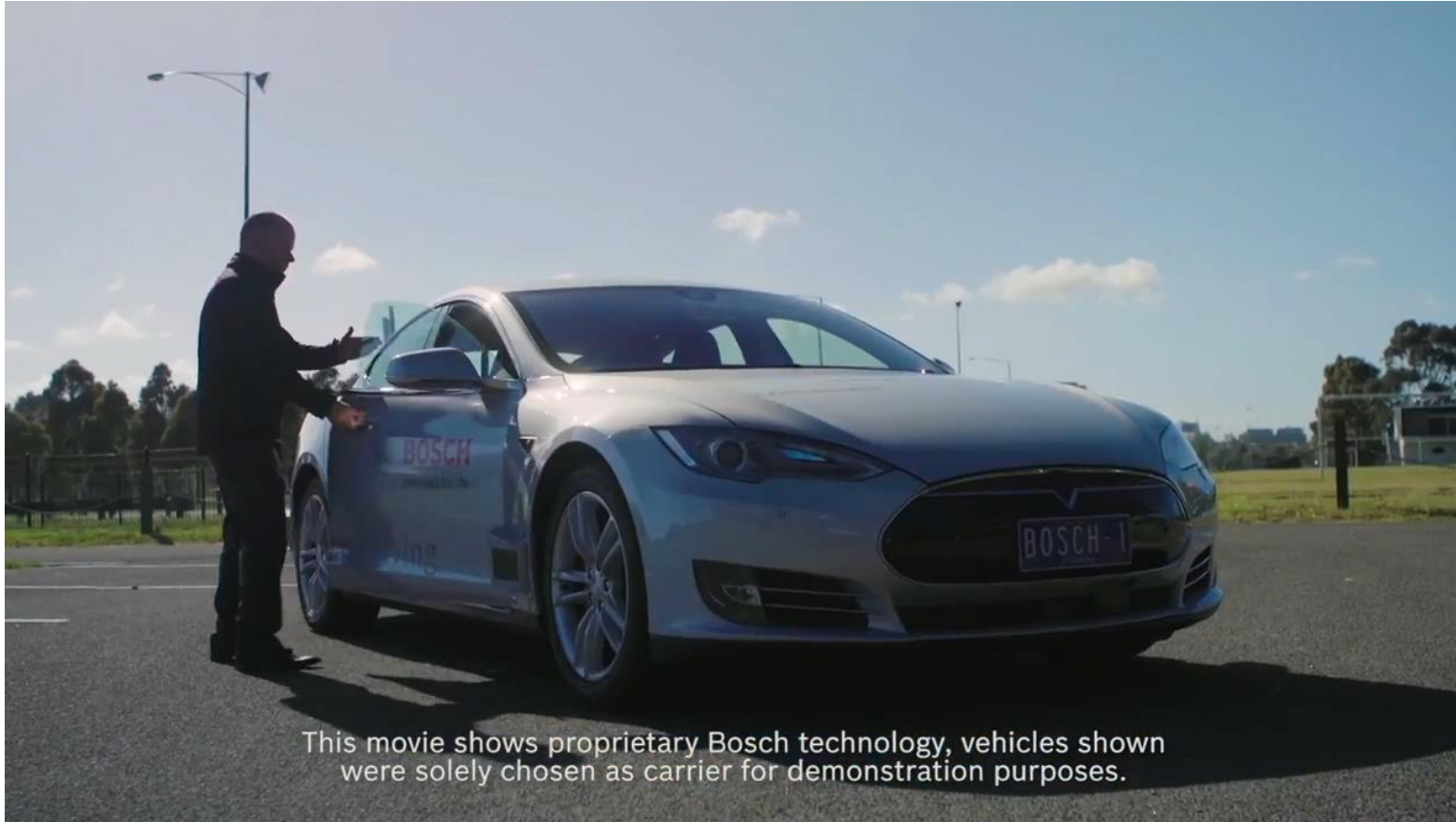


Alessandro Oltramari, Lisa Yu, Jon Francis (CR/RTC3.1)

Emilie Teitz (RBNA/HRC1.31 – trainee)

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“Marketing” Video



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AI limitations

Dynamic Environment



Perception

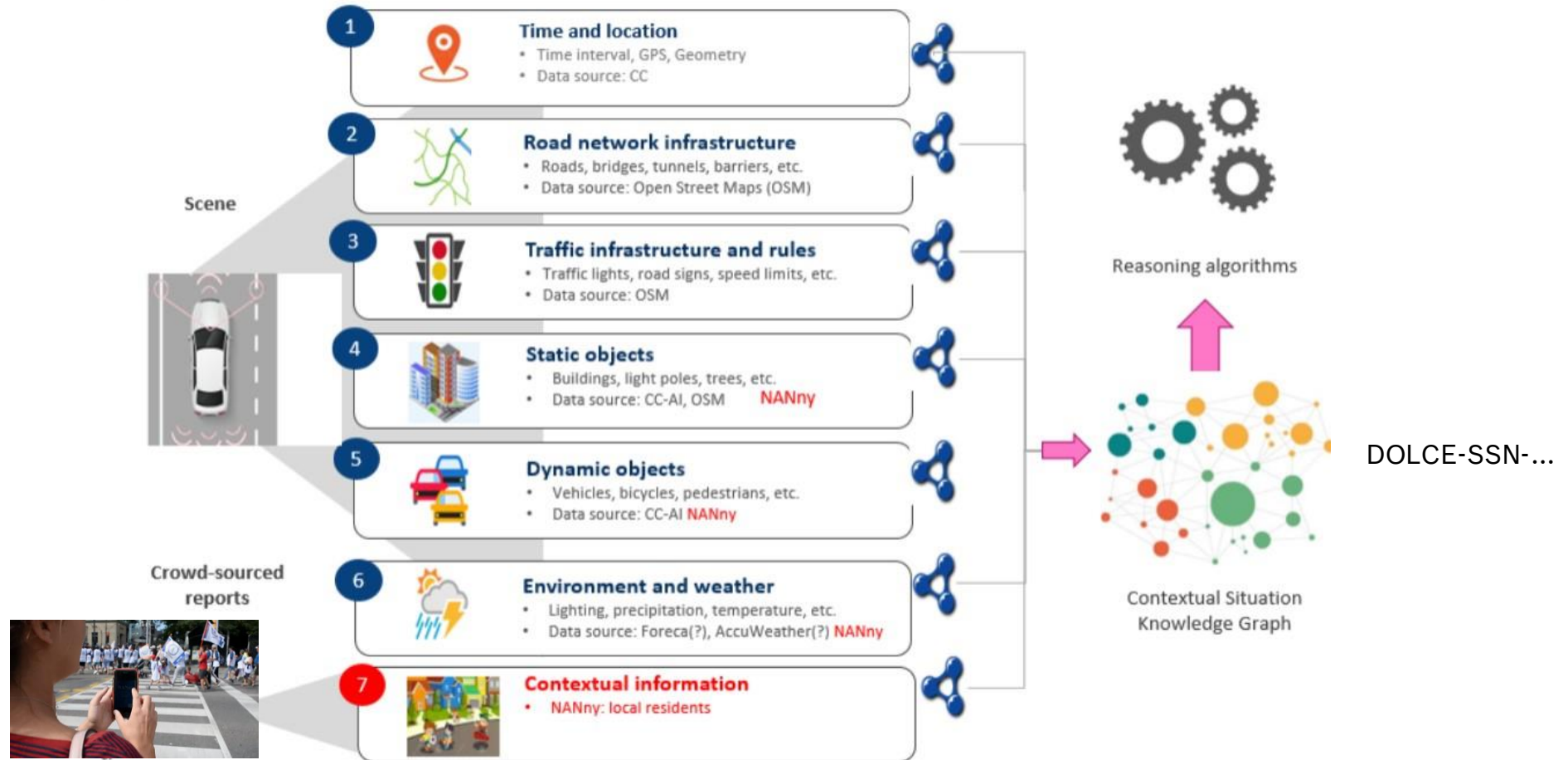


Behavior on the road



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Goal 1: Augmenting Data Analysis of Braking Events



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Goal 2 and 3: Supporting L4 Automation

Autonomous-to-Manual

Input: Frequent jay walkers in area due to Michigan Football Game.



“Frequent jay walkers in area. Take over vehicle in 20 seconds.”

Friction Mapping

Input: Low friction on roadway ahead due to water



“Low friction on roadway ahead. Vehicles brakes are now activated.”

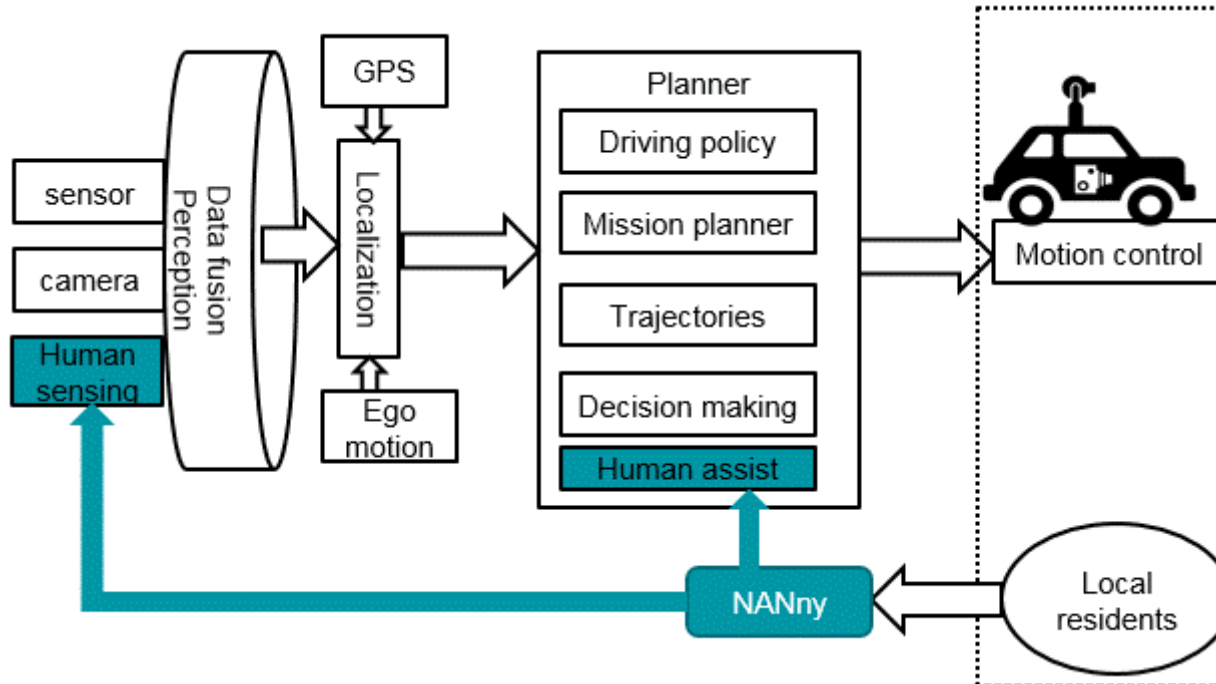
Input: Very low friction on roadway due to snow.



“Low friction on roadway ahead. Take over vehicle in 20 seconds.”

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Role of NANny in self-driving vehicles



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Conclusions

- ▶ This is just the beginning, not the conclusion
- ▶ Over the last three days I've seen fascinating theories, elegant axiomatizations
- ▶ It's ok
- ▶ But tackling the right problems in a sort of self-contained, self-referential way, hinders the (huge) impact that the FOIS community can have on AI today!
- ▶ The advent of Deep/Machine Learning, as the (brand) “new paradigm”, has opened new opportunities for our community: DL is a powerful, and yet flawed, paradigm!
- ▶ My prediction: the future of Applied Ontology, and of this conference, will be more and more focused on the integration between symbolic models and learning algorithms
- ▶ How about a FOIS out of FOIS-comfort-zone?
- ▶ Maybe in the future...

THANK
YOU!