SCOPE: Sensemaking in Cyber Social Spaces

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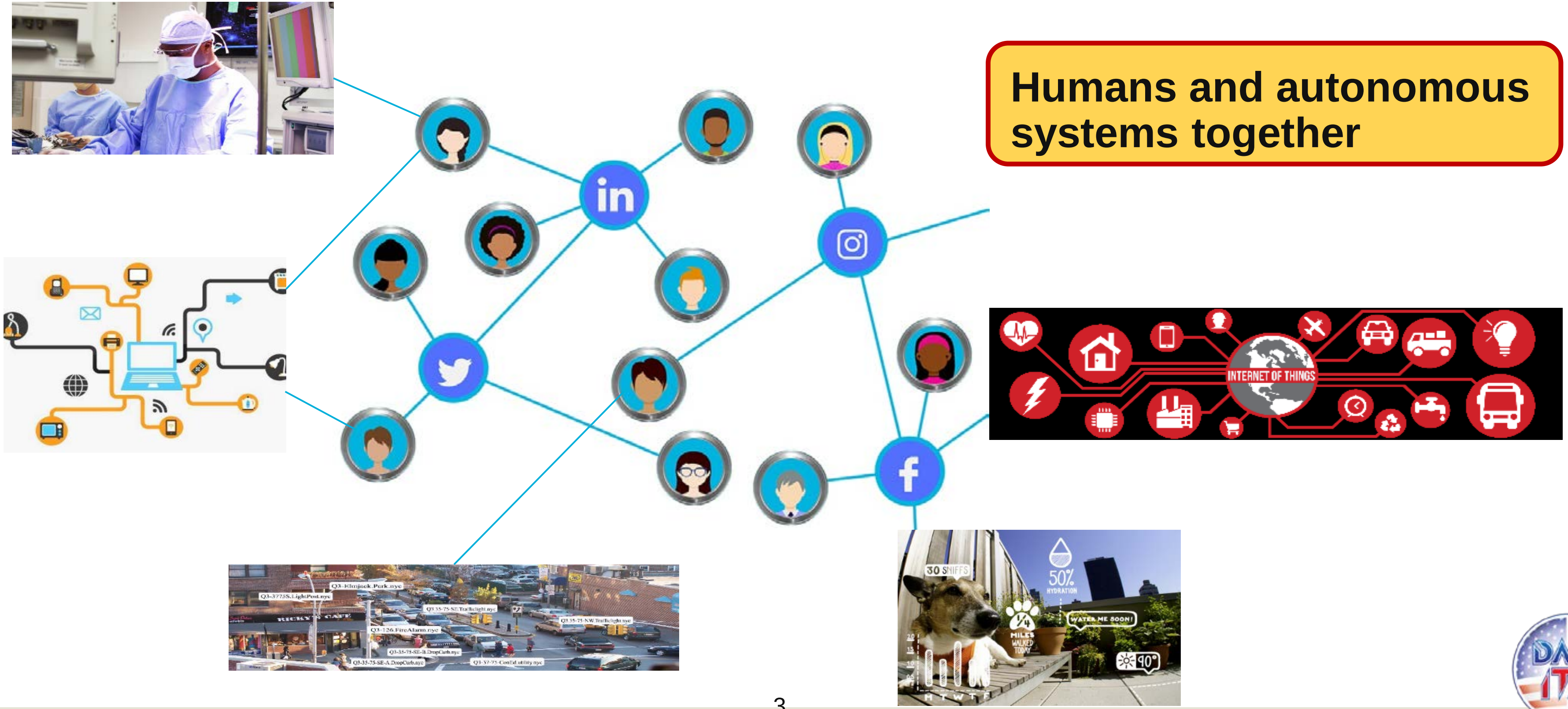
Overview

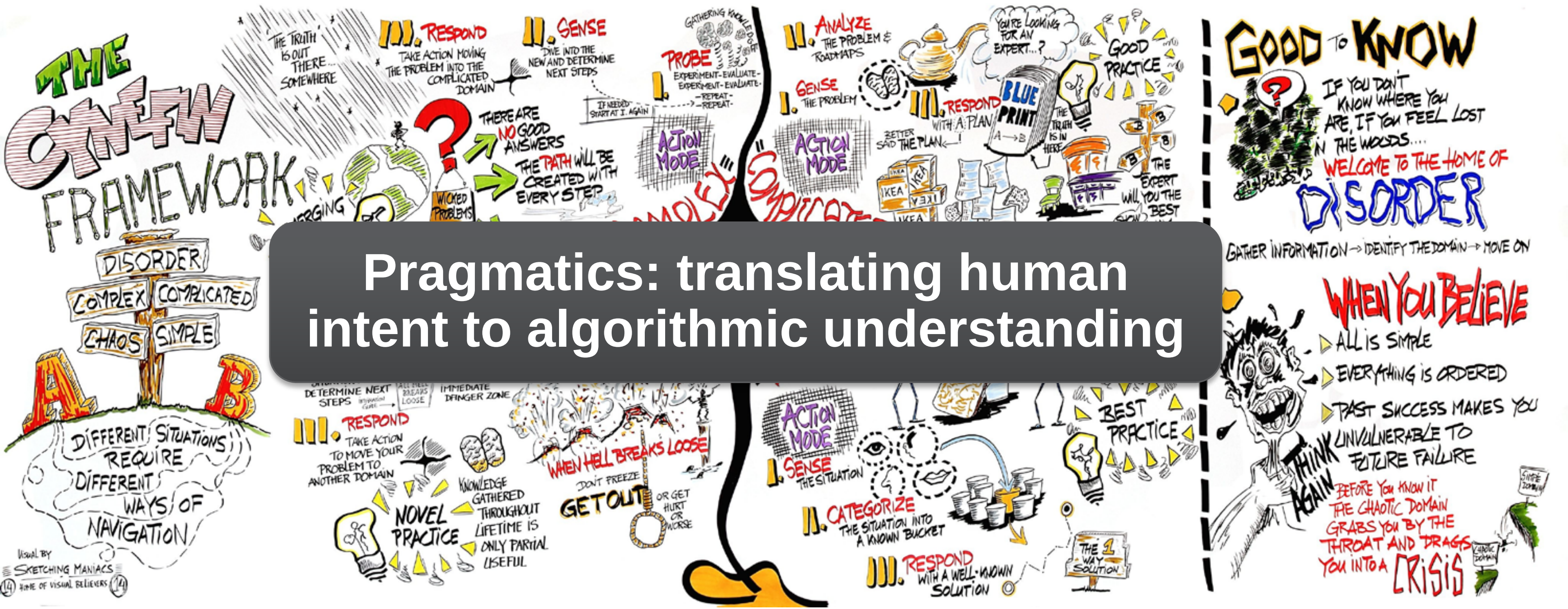
- What is a Cyber Social Space?
  - Humans and autonomous systems together
  - Sense making
    - Pragmatics
- Sense Making: An analogy to brain inspired compute
  - Distributed Brain
- Desired features of distributed brain for sensemaking in Cyber Social Spaces
- Conclusion: Looking ahead

Cyber Social Space

Humans and autonomous systems together



Sense Making

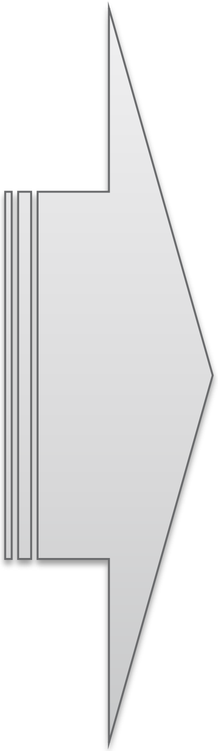


Pragmatics: translating human intent to algorithmic understanding

https://en.wikipedia.org/wiki/Cynefin_framework

Viswanathan, A., de Mel, G. and Hendler, J.A., 2018. Feature-based reformulation of entities in triple pattern queries. arXiv preprint arXiv:1807.01801.

A New Paradigm for Coalition Intelligence: A Distributed Brain



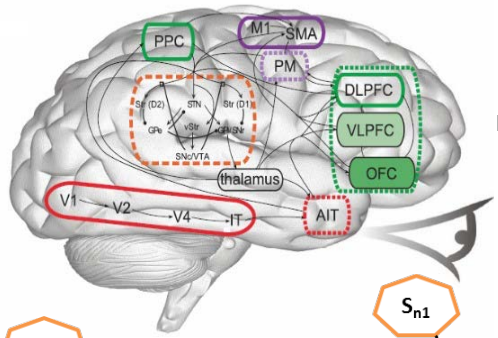
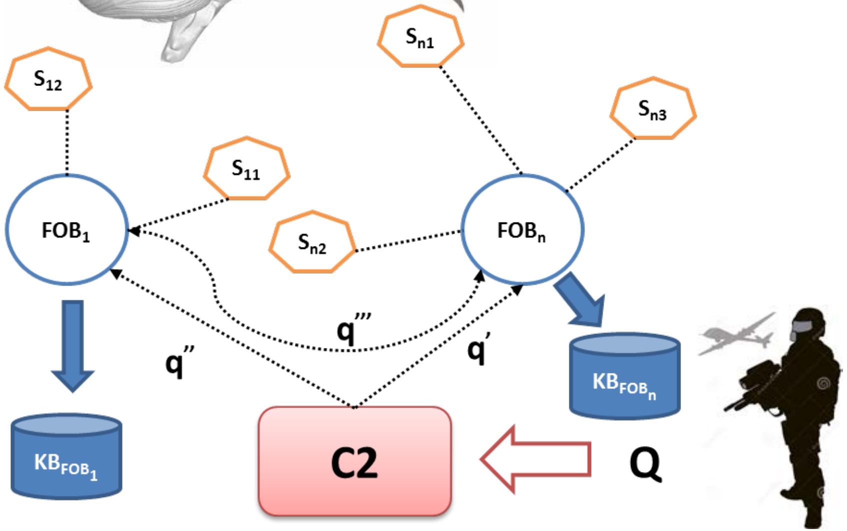


Image credit: **Chris Eliasmith**

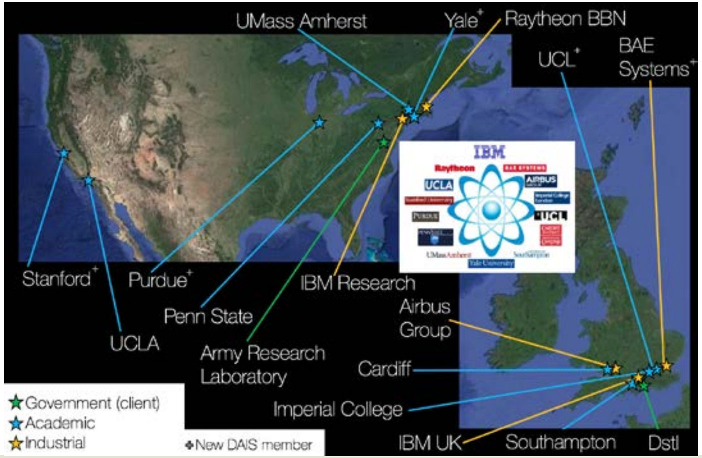


DAIS ITA—10 Year Fundamental Research Program

Dynamic Secure Coalition Infrastructures:

Distributed, dynamic, secure coalition communication/information infrastructures that support distributed analytics for situational understanding

- Software defined coalitions
- Generative policy models for coalitions
- Agile composition for coalition environments



Coalition Distributed Analytics and Situational Understanding:

Operating in complex multi-actor situations with high and complexity of data. Time-critical and sensitive information in a tactical environment, tailored to the needs of the human team members.

- Evolution of complex adaptive human systems
- Instinctive Analytics in a coalition environment
- Anticipatory Situational Understanding for coalitions

DAIS ITA: https://dais-ita.org/pub
Science Library: http://sl.dais-ita.org/science-library

Desired Features of Distributed Brain for Sensemaking

- Social signals as a sensing modality
- Intent inference and management
  - Emotions
  - Influence
- Autonomy
  - Learning
    - Learning from small data
- Explanations
  - Black- vs White- box reasoning
- Uncertainty quantification in ML

Murat Sensoy, Lance Kaplan, Melih Kandemir, Evidential Deep Learning to Quantify Classification Uncertainty, NIPS 2018 (Available at arXiv:1806.01768)

Jayarajah, K., Yao, S., Mutharaju, R., Misra, A., De Mel, G., Skipper, J., Abdelzaher, T. and Kolodny, M., 2015, October. Social signal processing for real-time situational understanding: A vision and approach. In *Mobile Ad Hoc and Sensor Systems (MASS), 2015 IEEE 12th International Conference on* (pp. 627-632). IEEE.

- Knowledge acquisition, representation, and reasoning

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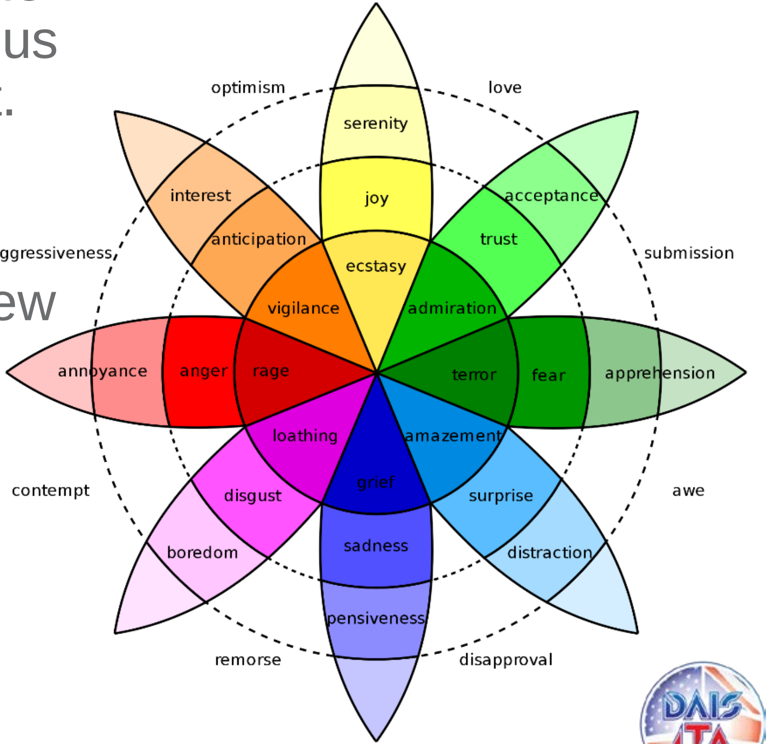
Fine-grained Emotion Mining

Collaboration: Annika Schoene (A.M.Schoene@2017.hull.ac.uk)

- Cyber social spaces have an impact on the the inferences users—be it humans or autonomous systems—make about their sounding context.
- As power of AI increases, the influence such systems will have on the network will be amplified, thus potentially polarise a social view or an outcome.
- State-of-the-art (e.g., SentiNet)
  - Polarities
  - Ekman's six basic emotions
- Plutchik's wheel of emotions
  - Dyads



Fine-grained Emotion Mining

Collaboration: Annika Schoene (A.M.Schoene@2017.hull.ac.uk)

- Data
  - NBC Russian chat bot data, 2016 U.S. elections
  - Weather Data, crowdflower, 2016
  - Stanford CS224N, 2009
- Approach
  - Lexicon-based approach for fine-grained emotion detection in tweets—both for text content and hashtags
    - EmoLex (National Research Council Canada (NRC) Emotion Word lexicon) https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm
  - Strategy to infer added emotions—i.e., dyads
    - Achieve 78.53% accuracy when compared to 34.46% SentiNet
  - Topic modelling using the emotions

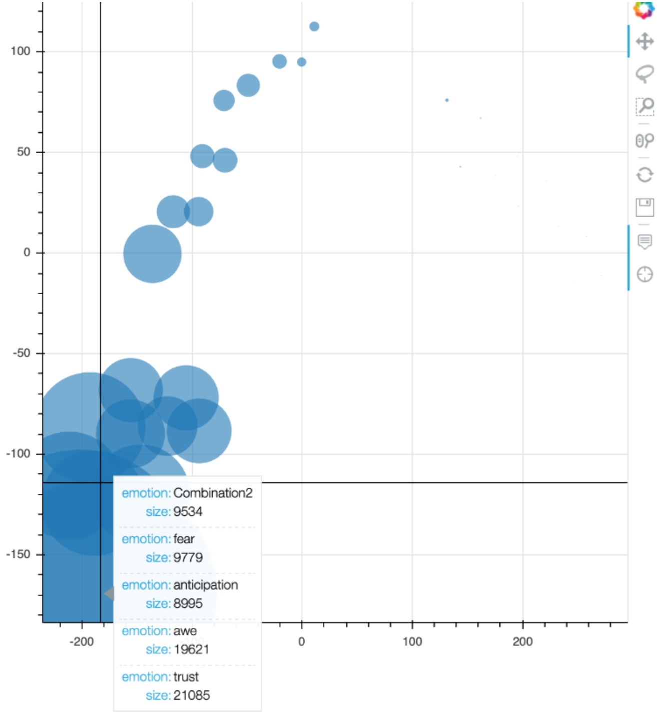
Fine-grained Emotion Mining

Collaboration: Annika Schoene (A.M.Schoene@2017.hull.ac.uk)

- Topic Modeling with Emotions
  - Tweets as separate documents
  - Author-Topic inspired Emotion-Topic Model
  - Pooling as means to cluster topics in emotion space.

Emotion	Weather Data	Russia Data	104K Data
Joy	sunshine/beautiful	Trump/supporter	love/baby
Trust	snow/patrol	president/Trump l	school/follower
Fear	tornado/hot	war/police	change/homework
Surprise	weather/chance	Trump/Donald	Trump/Donald
Sadness	weather/rainy	black/refugee	lost/cry
Disgust	cold/weather	Trump/Clinton	boy/crap
Anger	morning/patchy	Hillary/Obama/hit	hot/hit
Anticipation	time/storm/tomorrow	time/Trump/start	time/tomorrow
Love	sunshine/weather	Trump/Supporter	wonderful/smile
Submission	link/user	Clinton/Trump	hospital/hurt
Awe	morning/patchy day	Hillary/ #politics	good/day
Disapproval	storm/weather	Clinton/black/vote	no good/don't like
Remorse	hope/sunny/forecast	Trump/ #tcot	sick/shame
Contempt	window/freezing	Clinton/criminal	horrible/damn
Aggressiveness	weather/ storm	against/Hillary	day/get
Optimism	sunny/day	Trump/young/gift	good/hope

Table 5: Results Experiment 2 - Most common words for the most dominant topic



A Schoene, G de Mel, Pooling Tweets by Fine-Grained Emotions to Uncover Topic Trends in Social Media, Under review AAAI AIES 2019

Desired Features of Distributed Brain for Sensemaking

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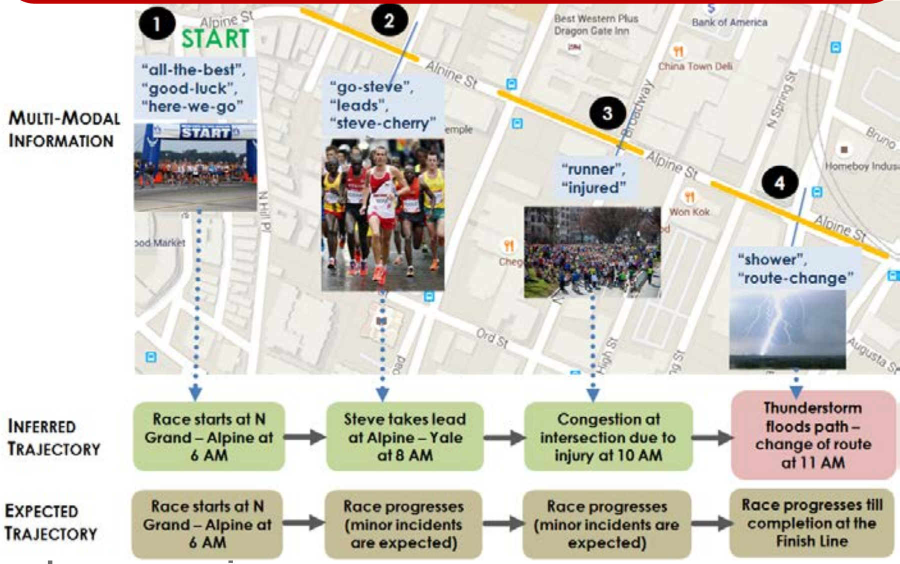
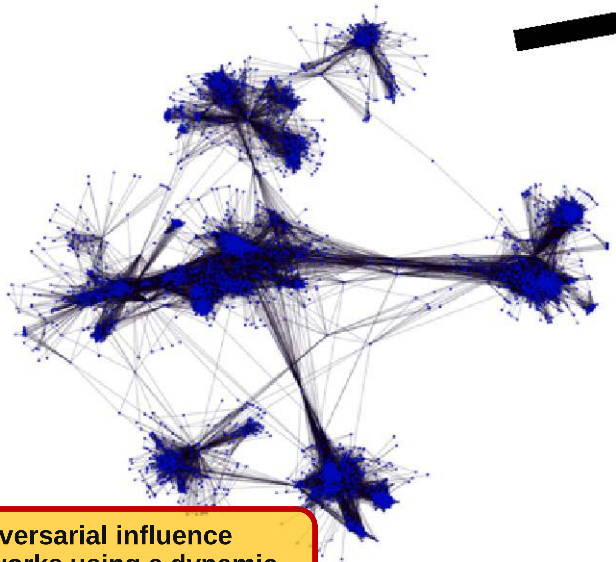
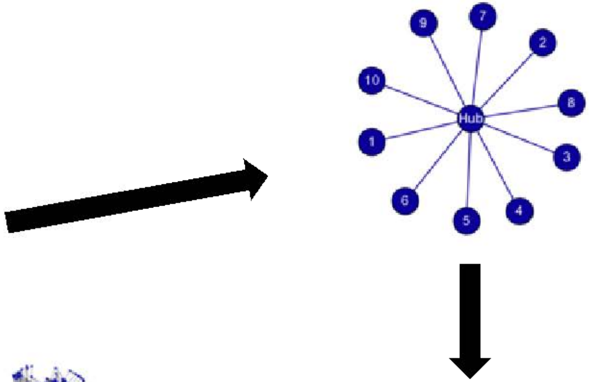


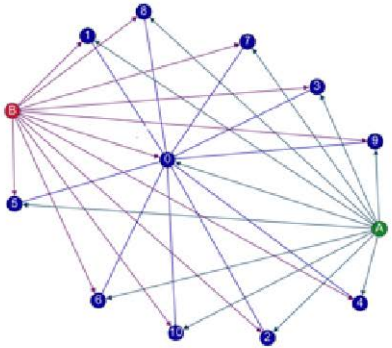
Influence Maximisation and Opinion Control

Collaboration: Schuh Chakraborty (sc8n15@ecs.soton.ac.uk), Sebastian Stein

- Network of choice







S Chakraborty, S. Stein, Adversarial influence maximisation in social networks using a dynamic model, in preparation for AAMAS 2019

Influence Maximisation and Opinion Control

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System Model

N: size of the system

n: no. of peripheral nodes

k_a: no. of peripheral nodes targeted by A

k_b: no. of peripheral nodes targeted by B

a: resource available to A ($p_{a,i/j}$)

b: resource available to B ($p_{b,i/j}$)

α: resource allotted by A to a peripheral node

β: resource allotted by B to a peripheral node

a-k_aα: resource allotted by A to the hub

b-k_bβ: resource allotted by A to the hub

$U_{a,i}$: state of node i wrt opinion A

Using Voter Dynamics:

$$\frac{du_{a,i}}{dt} = (1-u_{a,i})\frac{\sum_{j=1}^{N} u_{a,j} + p_{a,i}}{N + p_{a,i} + p_{b,i}} - u_{a,i}\frac{\sum_{j=1}^{N}(1-u_{a,j}) + p_{b,i}}{N + p_{a,i} + p_{b,i}}$$

At equilibrium,

$$\left[L + diag(p_{a,1}+p_{b,1}, \ldots., p_{a,N}+p_{b,N})\right]\begin{pmatrix} u_{a,1} \\ \cdot \\ \cdot \\ \cdot \\ u_{a,N} \end{pmatrix} = \begin{pmatrix} p_{a,1} \\ \cdot \\ \cdot \\ \cdot \\ p_{a,N} \end{pmatrix}$$

Influence Maximisation and Opinion Control

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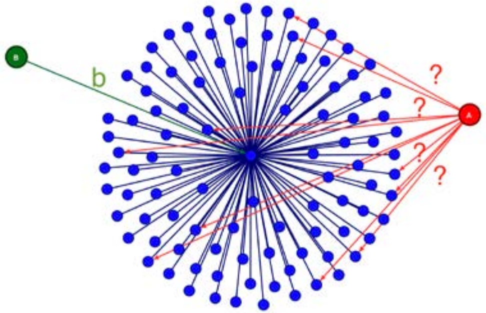
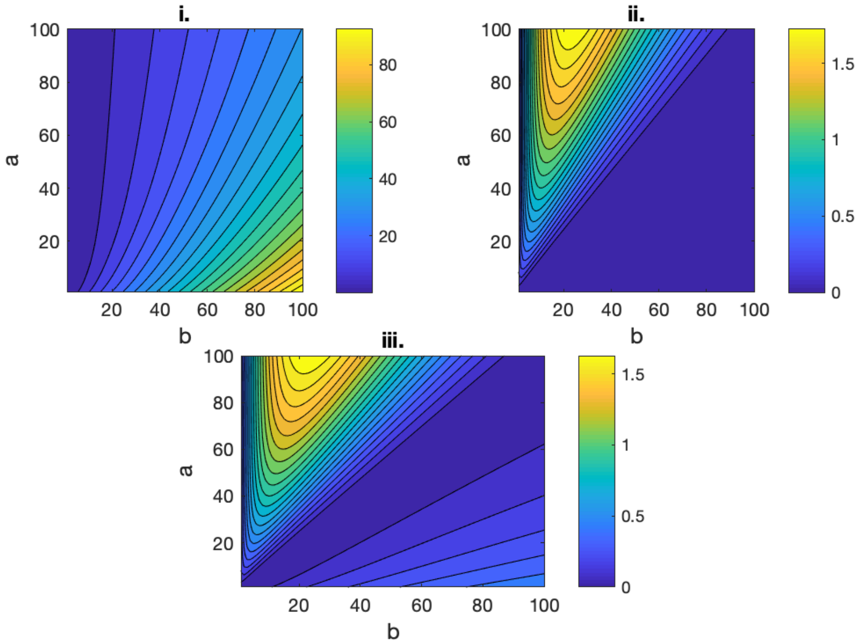
- Known Strategies



$$u_{a,hub} = u_{a,k+1\dots n+1} = \frac{a + a\alpha - k\alpha^2}{a\alpha + a + b\alpha + b - k\alpha^2}$$

$$u_{a,2..k} = \frac{a + a\alpha + b\alpha - k\alpha^2}{a\alpha + a + b\alpha + b - k\alpha^2}$$

$$u_{a,avg} = \frac{(n+1-k)u_{a,hub} + ku_{a,2..k}}{n+1} = \frac{a(\alpha+1)(n+1) - k\alpha(-b + n\alpha + \alpha)}{(n+1)(a\alpha + a + b\alpha + b - k\alpha^2)}$$



Heat maps showing the % gain in $u_{a,avg}$ when A plays the optimal strategy in comparison to(i) targeting the hub node, (ii) targeting the periphery and (iii) targeting all nodes randomly, against B targeting the hub for different values of available resources a and b.

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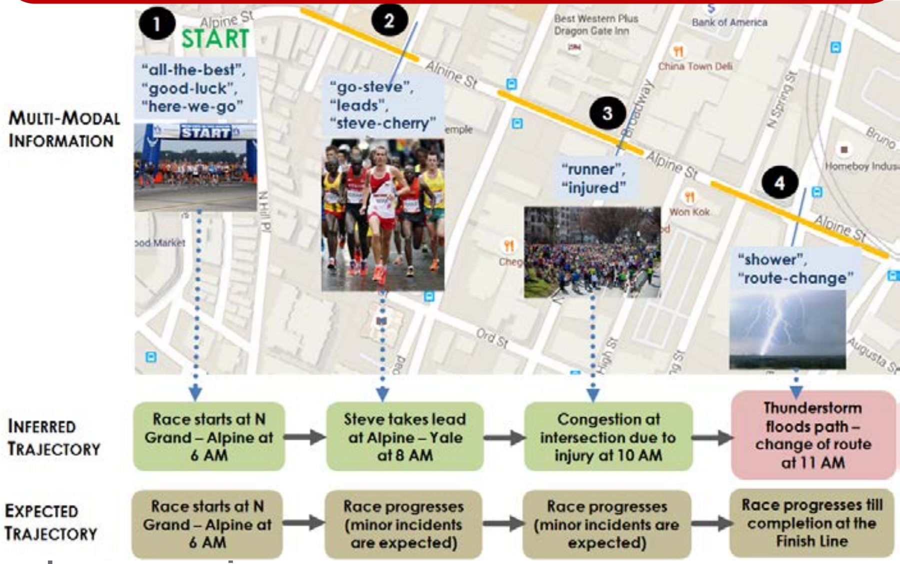


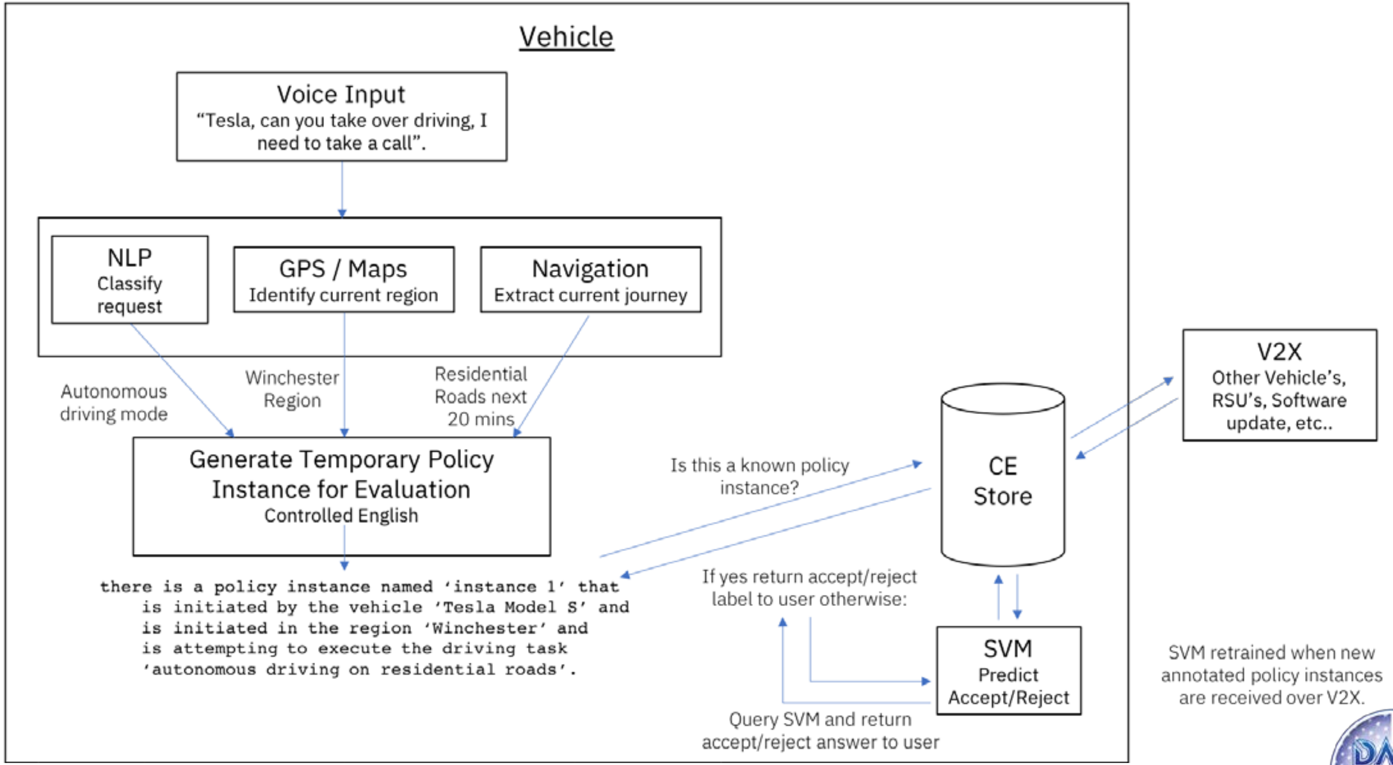
Constraint Learning in CAVs
Collaboration: Imperial College, IBM TJ Watson Center, IBM Research (UK)

- Generative Policy Models for Connected and Autonomous Vehicles (CAVs) based on Local Knowledge
  - Dynamic route planning
  - Crowdsourced Polices

- A knowledge-based approach to generate constraints
- Symbolic- and deep- learning approaches to generalise models from surrounding instances

Constraint Learning in CAVs
Collaboration: Imperial College, IBM TJ Watson Center, IBM Research (UK)

- Architecture

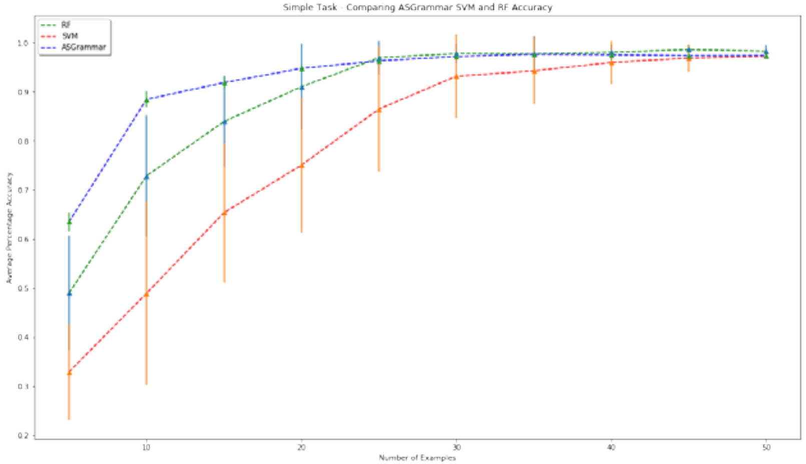


Constraint Learning in CAVs
Collaboration: Imperial College, IBM TJ Watson Center, IBM Research (UK)

SAE level	SAE name	SAE narrative definition	Execution of steering and acceleration/ deceleration	Monitoring of driving environment	Fallback performance of *dynamic driving task*	System capability (*driving modes*)
Human driver **monitors the driving environment**						
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
Automated driving system **("system") monitors the driving environment**						
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task* with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	**High Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

- Symbolic Learning over constraints

```
#modeba(vehicle_loa(var(int))):[1].
#modeba(region_loa(var(int))):[1].
#modeba(driving_task_loa(var(int))):[1].
#modebb(var(int) < var(int)):[1].
```

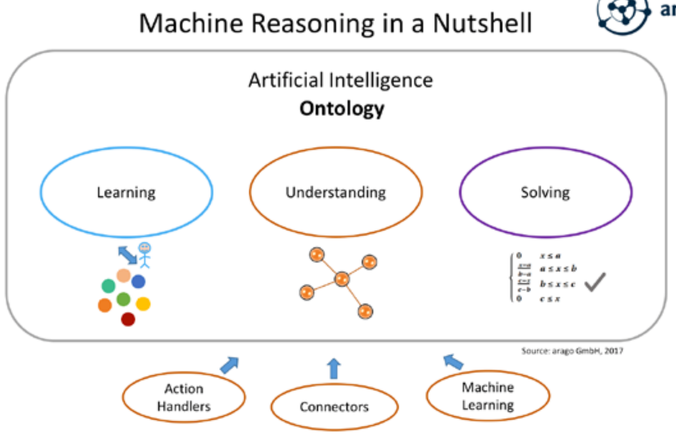


Conclusion: Looking ahead

- Deep learning with Symbolic Reasoning
- Model transferability
  - Healthily living to shopping
- Explanations
  - Biasness, Responsibility, Adaptation
- Uncertainty quantification in deep learning

all w.r.t. multimodal data and fusion engines

https://www.reasoning.world/ai-is-about-machine-reasoning-or-when-machine-learning-is-just-a-fancy-plugin/



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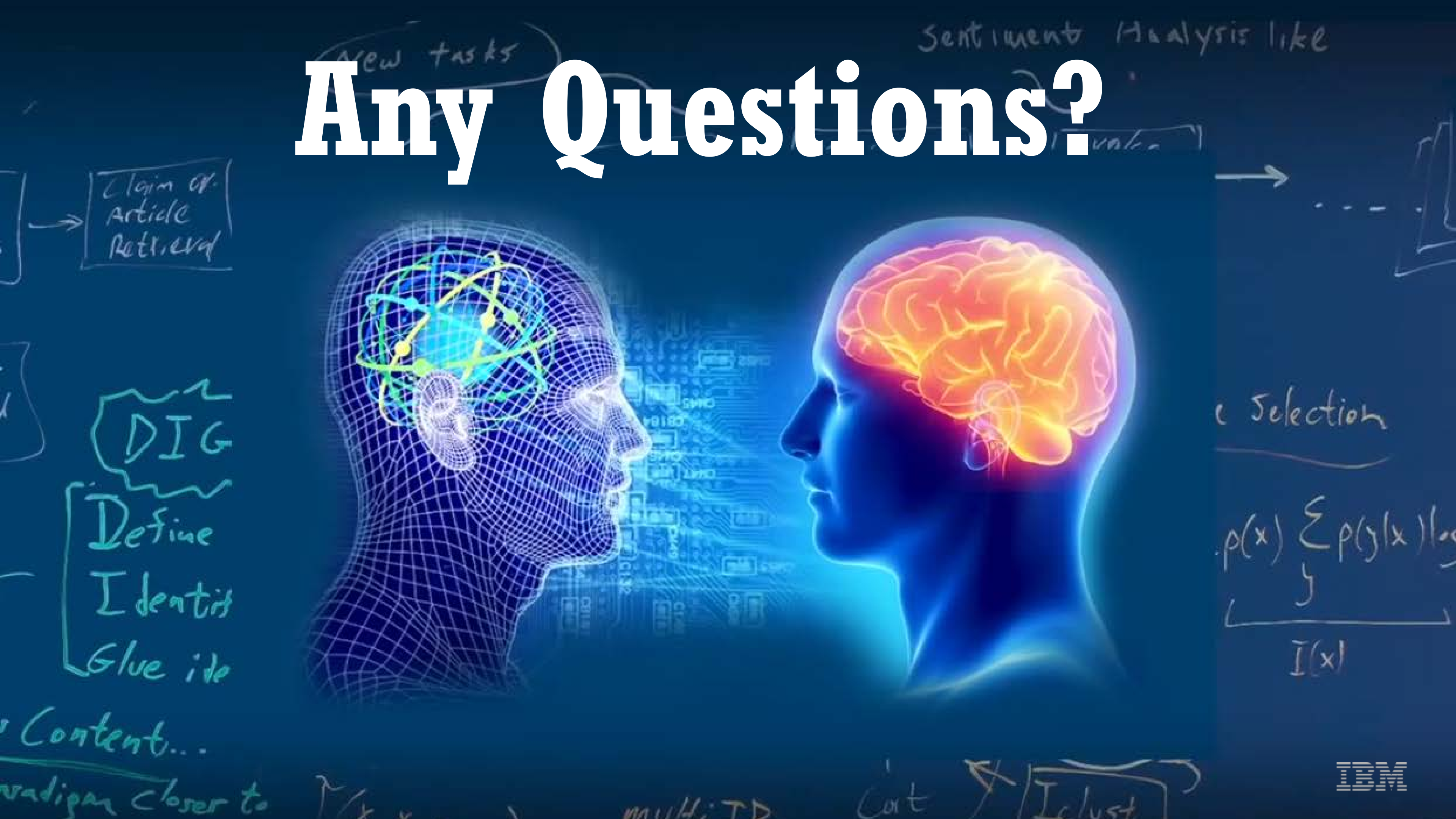
Acknowledgment

”This research was sponsored by the U.S. Army Research Laboratory and the U.K. Ministry of Defence under Agreement Number W911NF-16-3-0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the U.S. Army Research Laboratory, the U.S. Government, the U.K. Ministry of Defence or the U.K. Government. The U.S. and U.K. Governments are authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon.”

Any Questions?



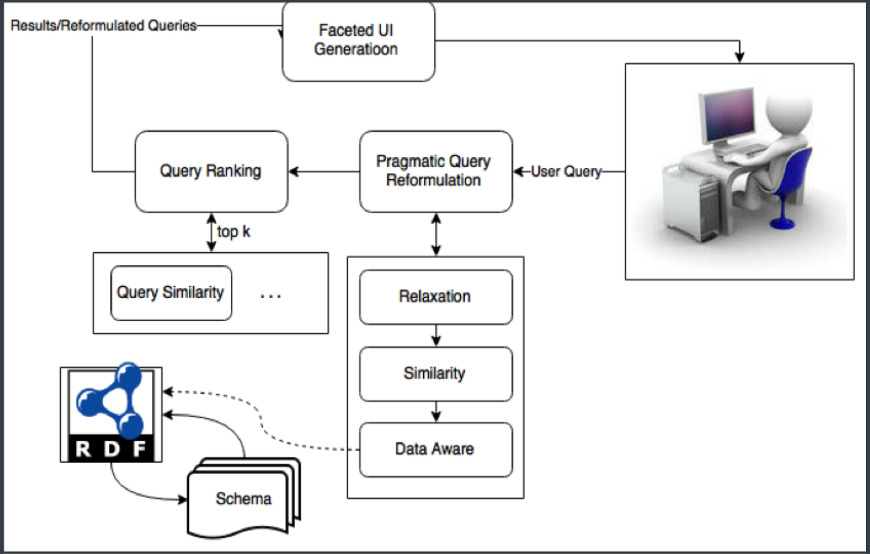
Backup

BULF: Pragmatically-aware Query Answering

Collaboration : RPI

Motivation: ⟨*Find all the things Martin Scorsese* is involved with, which translates into *dbr:Martin Scorsese ?property ?value*

Reformulation Architecture



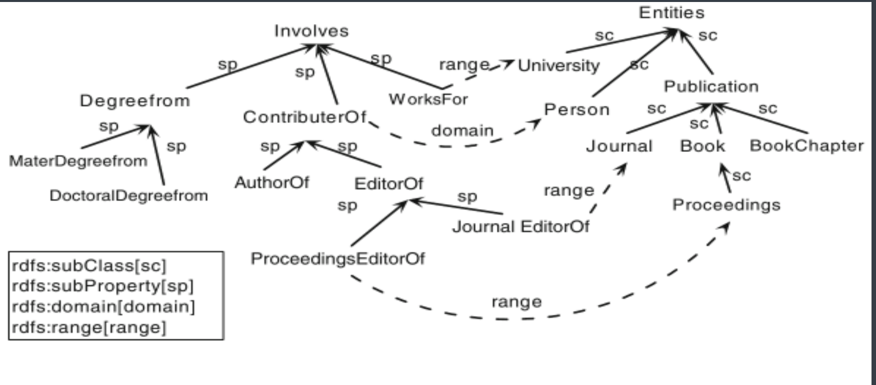


Figure 2: LUBM Ontology

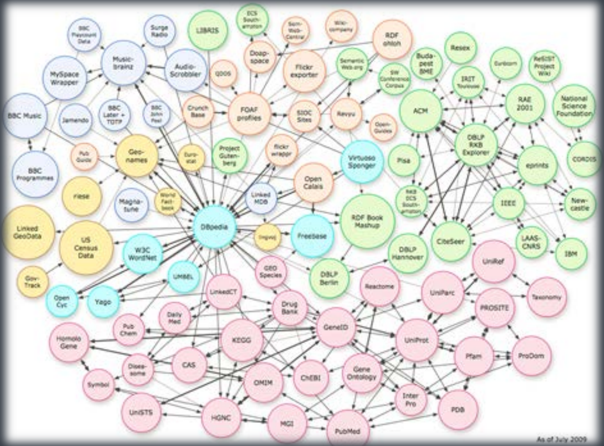
Initial results

Querying Knowledge Graphs

- Data represented as graphs.
- Edges represent relationships between nodes
- RDF Graphs are the most common Knowledge Graphs.

DBpedia

yago select knowledge



Query

```
SELECT ?X ?Y  WHERE {                              → HEAD
   ?X type VisitingProfessor .          (t1)
   ?X doctoralDegreeFrom ?Y .           (t2)       → BODY
}
```

- Query Failure → less than ***k*** results; $k \geq 0$

IBM

Existing Approach – Schema only Relaxation

Select name and email id of <Amar> whose nationality is <Pakistan> and is a student of AssistantProfessor whose dept is ?Z

Figure one failing condition

…name and email id of <Amar> whose nationality is ?Y and is a student of AssistantProfessor whose dept is ?Z1 .

… of a ?X whose nationality is ?Y and is a student of AssistantProfessor…

Figure second failing condition
Professor from Schema

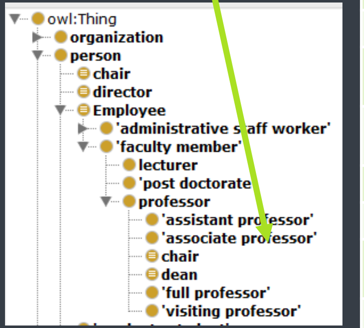
… of a ?X whose nationality is ?Y and is a student of any Professor . ⟹ First Valid Relaxation

Results < k, so keep Relaxing

… of a ?X whose nationality is ?Y and is a student of ?Z…

Drawback…

```
SELECT ?X ?Y  WHERE {
  ?X type PostDoc .                (t1)
  ?X doctoralDegreeFrom ?Y .       (t2)
}
```



Present in Schema

Subject	Predicate	Object
John	type	VisitingProfessor
John	worksFor	Purdue
John	researchInterest	Machine Learning
John	doctoralDegreeFrom	Cornell
Alex	type	FullProfessor
Alex	worksFor	Purdue
Alex	researchInterest	Machine Learning
Alex	doctoralDegreeFrom	RPI
VisitingProfessor	subClassOf	FullProfessor

Absent in Data

Schema Data agnostic.

Schema Awareness

So <Amar> $\xrightarrow{\text{Relax}}$?X

So <Pakistan> $\xrightarrow{\text{Relax}}$?Y

Instance Data	Rule
<Amar>	Relax to Variable
<Pakistan>	Relax to Variable

Instance Data agnostic.

Data Awareness

Our Reformulation Strategy

Select name and email id of <Amar> whose nationality is <Pakistan> and is a student of AssistantProfessor whose dept is ?Z

Address the Failed Conditions first

Data reformulation on <Pakistan>

Schema reformulation on AssistantProfessor

..name and email id of <Amar> whose nationality is a Country from Asia and is a student of Professor whose dept is ?Z1

.

First Valid Relaxation

Results < k, so keep Reformulating

Data reformulation on <Amar>

… of a ?X who works on Query Reformulation whose nationality is a Country from Asia and is a student of Professor …

… of a ?X who works on Query Reformulation whose nationality is a Country from Asia and is a student of ?X who is in TW

Takeaway : Instances are described by their predicates

Top-k Predicates

In real life datasets, instances have a lot of properties.

dbr:Martin_Scorsese

predicate	object
dbp:almaMater	dbr:Tisch_School_of_the_Arts
rdf:type	dbc:American_film_directors
dbp:occupation	"Film director, producer, actor, screenwriter"
rdf:type	dbc:English-language_film_directors
…	…
181 predicates	

```
SELECT ?birthPlace WHERE {
   dbr:Martin_Scorsese a yago:AmericanFilmDirectorsOfItalianDescent
   dbr:Martin_Scorsese dbo:birthPlace ?birthPlace .
}
```

- Adding all the 181 predicates is not possible.
- Not all properties are important.
- The need to pick Top-k properties.