A low-angle shot of a Ferris wheel cabin, likely the Big Wheel in Tel Aviv, against a clear blue sky. The cabin is white with large glass windows and is suspended from a complex network of white metal beams. The number '8' is visible on the side of the cabin. The lighting is bright, suggesting a sunny day.

The Neuro-Conceptual Approach to AI: When Deep Learning Meets Conceptual Modeling, Good Things Happen

Dov Dori

Faculty of Data and Decision Sciences

Technion, Israel Institute of Technology

ICORES 2025, Feb. 24, Porto, Portugal (virtual presentation)

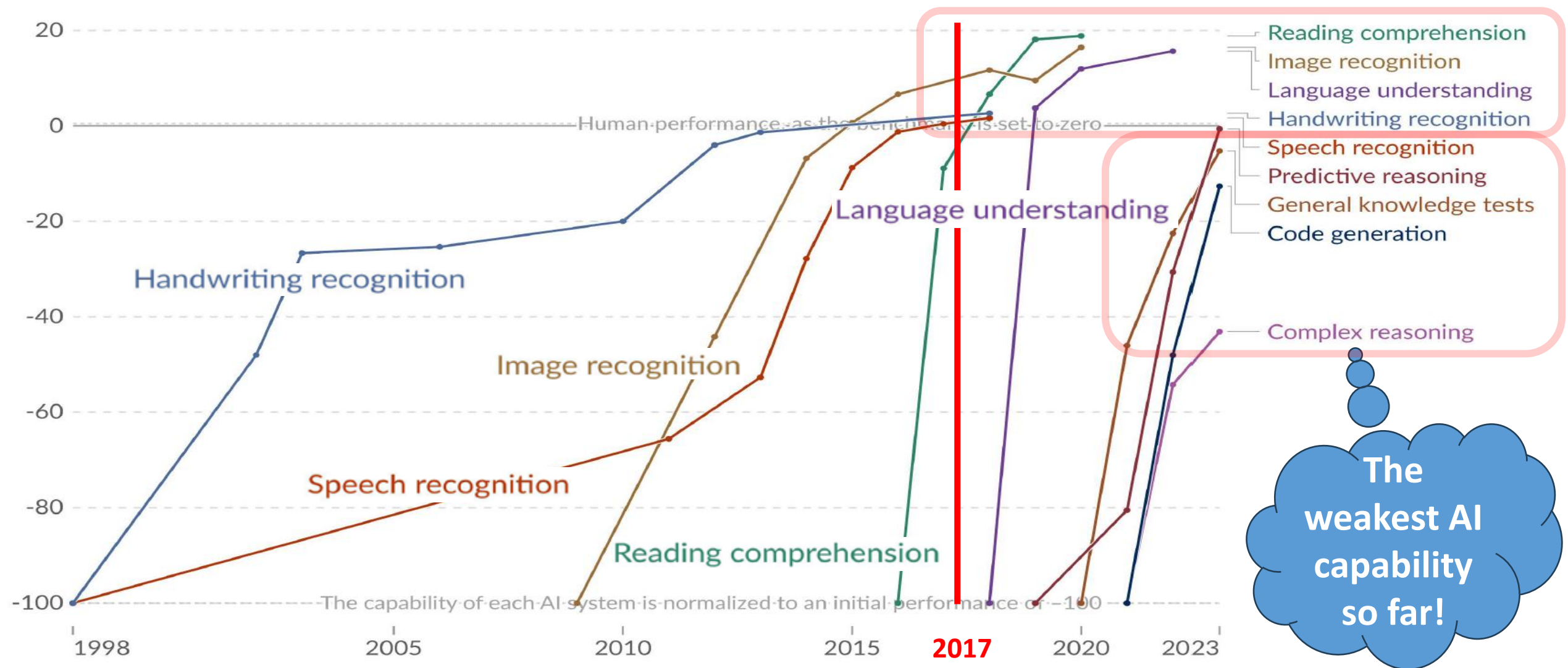
Joint work with Yulia Skolnik, Veronika Shteingardt, and Shahf Rocker-Yoel

A low-angle shot of a Ferris wheel cabin, showing its metallic structure and glass windows. The cabin is suspended from a large metal arm. The background is a clear blue sky with some light clouds. The cabin has a small number '8' on its side.

Talk Outline

- **Gen-AI: Impact and experience**
- **Conceptual modeling; OPM**
- **Model-Based Systems Engineering**
- **Neuro-Conceptual AI**
- **Converting text to model**
- **Evaluation and potential impact**

Human vs. AI capabilities



The weakest AI capability so far!

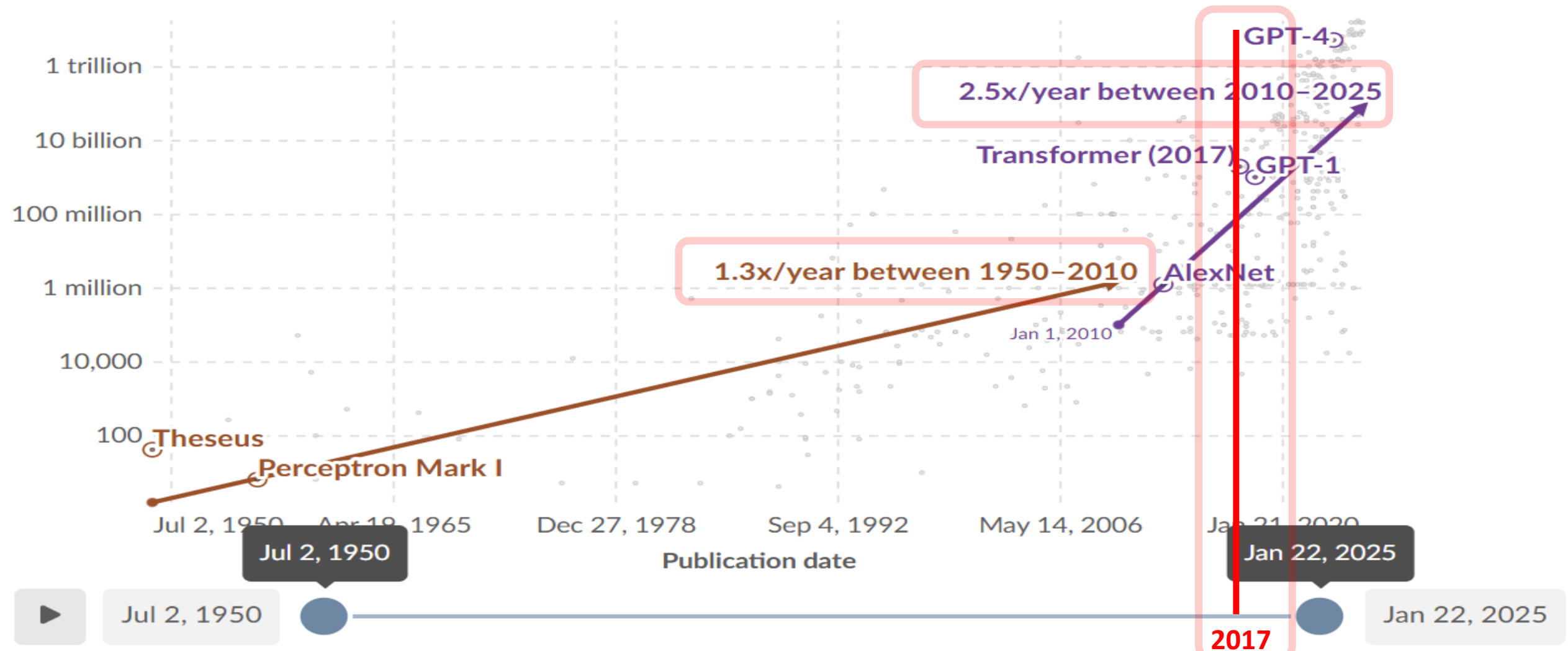
Data source: Kiela et al. (2023)

OurWorldinData.org/artificial-intelligence | CC BY

Note: For each capability, the first year always shows a baseline of -100, even if better performance was recorded later that year.

Training dataset size has grown hyper-exponentially

Training datapoints (datapoints)



What happened in 2017?

Attention Is All You Need

[PDF] [Attention is all you need](#)

[A Vaswani](#) - Advances in Neural Information Processing Systems, 2017 - [huggingface.co](#)

Attention is all you need Attention is all you need ...

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Feb. 24, 2025 – 3 weeks later
762/day

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to

The **attention mechanism** allows the LLM to decide which **words** in the text **to focus on** specifically, according to their **importance** in the given **context**.

Let's examine some capabilities of Gen-AI

An example MATH question asked of the AI.

Hendryks et al./AI Index
2024

Problem: The equation $x^2 + 2x = i$ has two complex solutions. Determine the product of their real parts.

Solution: Complete the square by adding 1 to each side. Then $(x + 1)^2 = 1 + i = e^{\frac{i\pi}{4}} \sqrt{2}$, so $x + 1 = \pm e^{\frac{i\pi}{8}} \sqrt[4]{2}$. The desired product is then $(-1 + \cos(\frac{\pi}{8}) \sqrt[4]{2})(-1 - \cos(\frac{\pi}{8}) \sqrt[4]{2}) = 1 - \cos^2(\frac{\pi}{8}) \sqrt{2} = 1 - \frac{(1 + \cos(\frac{\pi}{4}))}{2} \sqrt{2} = \boxed{\frac{1 - \sqrt{2}}{2}}$.

I wanted to know why

$$1 + i = e^{\frac{i\pi}{4}} \sqrt{2}$$


So I asked Claude:

“prove this:”

and I then pasted the piece I copied from the screen.

Here is what I got:



Claude  Evaluating the Complex Number $1+i$ 

$$1 + i = e^{\frac{i\pi}{4}} \sqrt{2}$$

DD prove this:

Let me prove that $1 + i = e^{(i\pi/4)}\sqrt{2}$ step by step.

1. First, let's recall Euler's formula: $e^{i\theta} = \cos(\theta) + i\sin(\theta)$
2. In our case, $\theta = \pi/4$, so: $e^{i\pi/4} = \cos(\pi/4) + i\sin(\pi/4)$
3. We know that for $\pi/4$ (45 degrees): $\cos(\pi/4) = 1/\sqrt{2}$ $\sin(\pi/4) = 1/\sqrt{2}$
4. Therefore: $e^{i\pi/4} = 1/\sqrt{2} + i/\sqrt{2}$
5. Now, $e^{i\pi/4}\sqrt{2} = (1/\sqrt{2} + i/\sqrt{2})\sqrt{2} = 1 + i$

This proves that $1 + i = e^{(i\pi/4)}\sqrt{2}$

We can verify this another way:

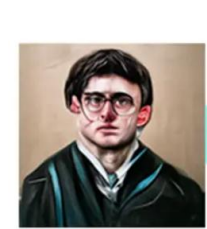
- We know $|1 + i| = \sqrt{2}$ (the modulus)
- The argument of $1 + i$ is $\pi/4$ (as $\arctan(1/1) = \pi/4$)
- This matches the polar form $r \cdot e^{i\theta}$ where $r = \sqrt{2}$ and $\theta = \pi/4$

Therefore, $1 + i = e^{(i\pi/4)}\sqrt{2}$

Gen-AI: Image generation evolution and capabilities

Midjourney generations over time: “a hyper-realistic image of Harry Potter”

Source: [Midjourney, 2023](#)



V1, February 2022



V2, April 2022



V3, July 2022



V4, November 2022



V5, March 2023



V5.1, March 2023



V5.2, June 2023



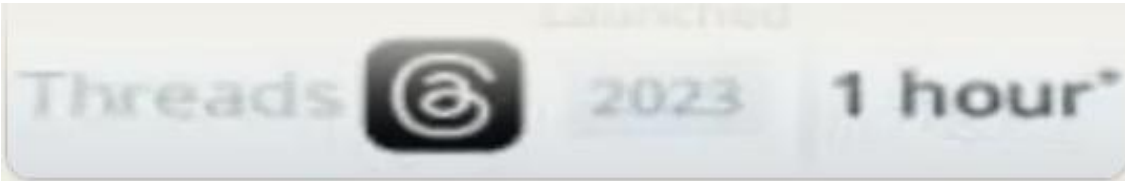
V6, December 2023

AI now surpasses humans in almost all performance benchmarks

Time to one million users



I was wondering about “Threads” so I asked Claude:



DD explain this

This appears to be a reference to "Threads," a social media platform that was launched by Meta (formerly Facebook) in 2023. The image shows what looks like a logo for Threads and indicates it launched in 2023 with "1 hour" noted (possibly referring to how quickly it gained users after launch).

Threads was indeed launched in July 2023 as Meta's competitor to Twitter/X. It was notable for gaining over 30 million sign-ups within its first day of launch, making it one of the fastest-growing apps in history. The platform was designed to be interoperable with the "fediverse" and integrated with Instagram's user base.

Am I so uninformed?

DD why is it less known?

Threads initially had a strong launch with millions of users signing up quickly, but several factors contributed to its reduced prominence:

1. Declining engagement after initial hype - many users signed up due to curiosity but didn't remain active regular users
2. Limited features at launch - the platform was missing key features that users expected from social media, like a web version (which came later), hashtags, and robust search
3. Regional availability issues - it wasn't immediately available in the EU due to regulatory concerns
4. Strong competition - while it aimed to capitalize on Twitter/X's controversial changes, other alternatives like Mastodon and Bluesky also emerged

With such stunning capabilities, why is complex reasoning so difficult for gen-AI?

- Reading comprehension
- Image recognition
- Language understanding
- Handwriting recognition
- Speech recognition
- Predictive reasoning
- General knowledge tests
- Code generation

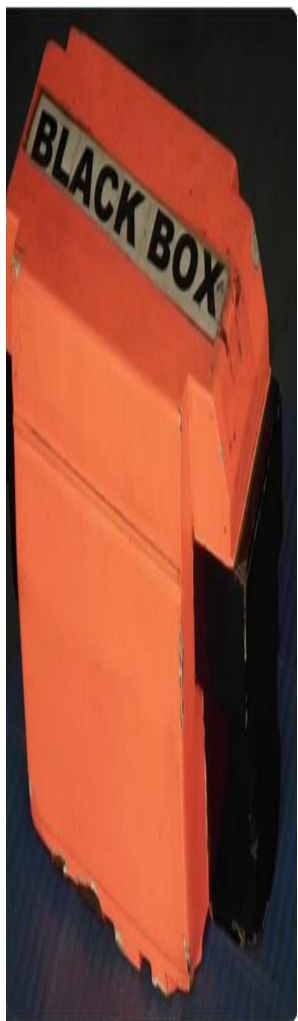
Complex reasoning



Main problems in deep learning and LLMs

Black Box

- Deep learning processes are opaque – very hard to analyze.
- Very difficult to tell how the LLM made its decisions.
- Complex reasoning poses huge challenge in interpretation.
- Especially problematic in mission-critical domains:
 - Medicine
 - Finance
 - Education
 - Security



Hallucinations

- The model can make up claims that are not true but presents them as facts.
- This undermines LLMs' credibility.
- Prevents using deep learning in mission-critical domains.



Claude can add insights to the slide I just presented:

Main problems in deep learning and LLMs

Black Box

- ❑ Deep learning processes are opaque – very hard to analyze.
- ❑ Very difficult to tell how the LLM made its decisions.
- ❑ Complex reasoning poses huge challenge in interpretation.
- ❑ Especially problematic in mission-critical domains:
 - ❑ Medicine
 - ❑ Finance
 - ❑ Education
 - ❑ Security

Hallucinations

- ❑ The model can make up claims that are not true but presents them as facts.
- ❑ This undermines LLMs' credibility.
- ❑ Prevents using deep learning in mission-critical domains.

DD explain this:

This image outlines two major challenges in deep learning (LLMs):

1. The "Black Box" Problem:

- Deep learning systems operate in ways that are opaque
- It's challenging to understand exactly how an LLM reaches its conclusions
- Complex reasoning within these systems is particularly hard to interpret
- This lack of transparency is especially concerning in critical fields like:
 - Medicine, where decisions could affect patient care
 - Finance, where decisions impact financial stability

- Education, where learning outcomes are at stake
- Security, where reliable decision-making is crucial

2. The Hallucination Problem:

- LLMs can generate false information while presenting it confidently as fact
- This tendency to "hallucinate" damages the overall credibility of LLM systems
- The risk of false information makes it particularly dangerous to use these systems in mission-critical applications where accuracy is essential

These challenges are interrelated - the black box nature of these systems makes it harder to prevent or detect hallucinations, while the tendency to hallucinate makes it more problematic that we can't fully understand how these systems work. This creates significant barriers to deploying these technologies in situations where reliability and transparency are crucial.

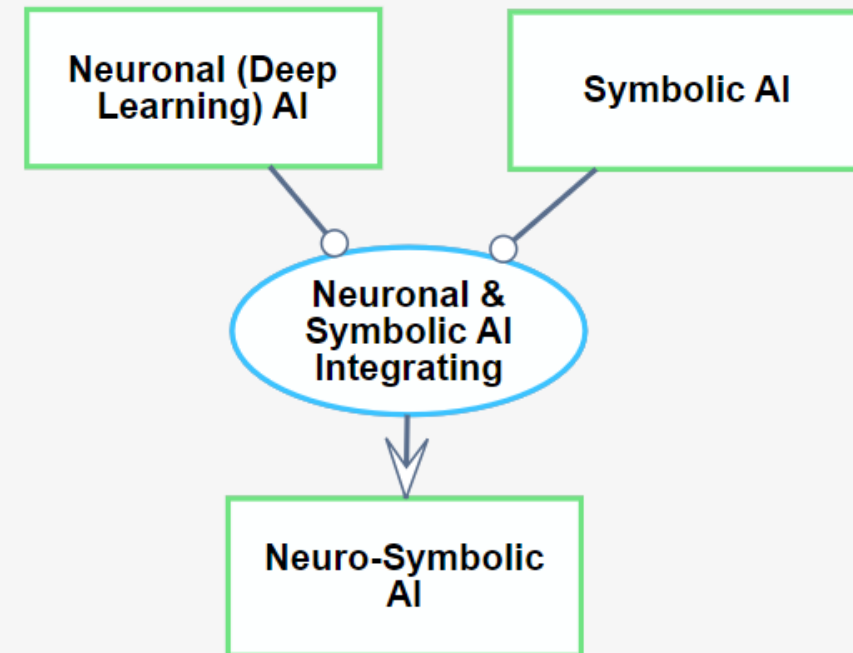
What can be done about black box and hallucinations?

The Neuro-Symbolic Approach to AI



NEURO-SYMBOLIC ARTIFICIAL INTELLIGENCE: THE STATE OF THE ART

Edited by
Pascal Hitzler



OPL

Neuronal & Symbolic AI Integrating requires Neuronal AI and Symbolic AI.
Neuronal & Symbolic AI Integrating yields Neuro-Symbolic AI.

The Neuro-Symbolic Approach – Benefits

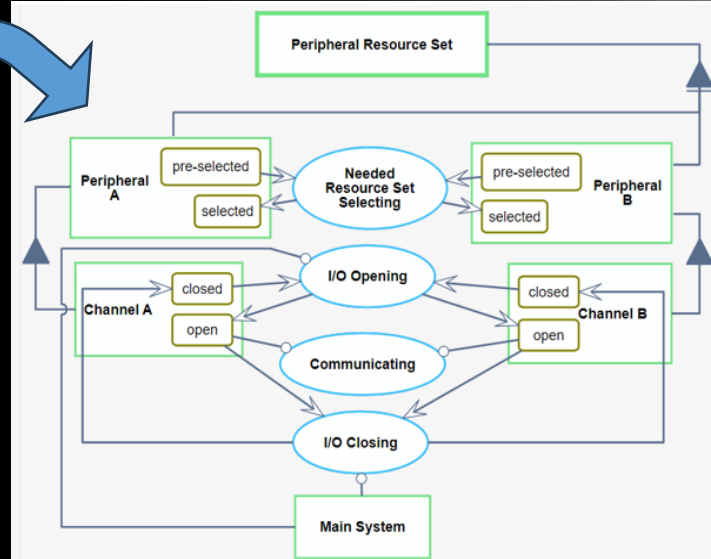
1. Combines neural networks' **deep learning** abilities with **symbolic reasoning's** logic and rules
2. Gives AI systems both the ability to **learn from data** and perform explicit **logical reasoning**
3. **Addresses limitations** of pure neural networks and pure symbolic systems
 - ❑ by creating hybrid architectures that **leverage the strengths of both approaches**
4. Enables **better interpretability** and **explainability**:
 - ❑ The symbolic component can provide logical traces of **reasoning**,
 - ❑ while still maintaining the **adaptability** and pattern recognition of **neural networks**
5. Shows promise in tasks requiring both **intuitive pattern matching** and **logical reasoning**: complex problem solving, natural language understanding, automated theorem proving...



Neuro-Conceptual AI – a subfield of Neuro-Symbolic AI

Combines two underlying technologies:

- ▶ **Large Multimodal Models (LMMs)**
 - ▶ *Integrate text, images, video, and voice*
 - ▶ *Enrich and contextualize knowledge using deep learning*
 - ▶ **PROBLEM: Lack of explainability (black box, hallucinations)**
- ▶ **Conceptual Modeling based on OPM – Object-Process Methodology ISO 19450**
 - ▶ *One of the two leading model-based systems engineering (MBSE) languages*
 - ▶ *Recently released as ISO 19450:2024*
 - ▶ **PROBLEM: Lack of automation -> requires human intellect**



Model-based systems engineering (MBSE):

The use of conceptual models to support system requirements, design, analysis, verification and validation activities throughout the system lifecycle.

In this paradigm, **the model is the authoritative source of truth**

Applications:

- ✓ MBSE
- ✓ Knowledge management
- ✓ ...

A conceptual model:

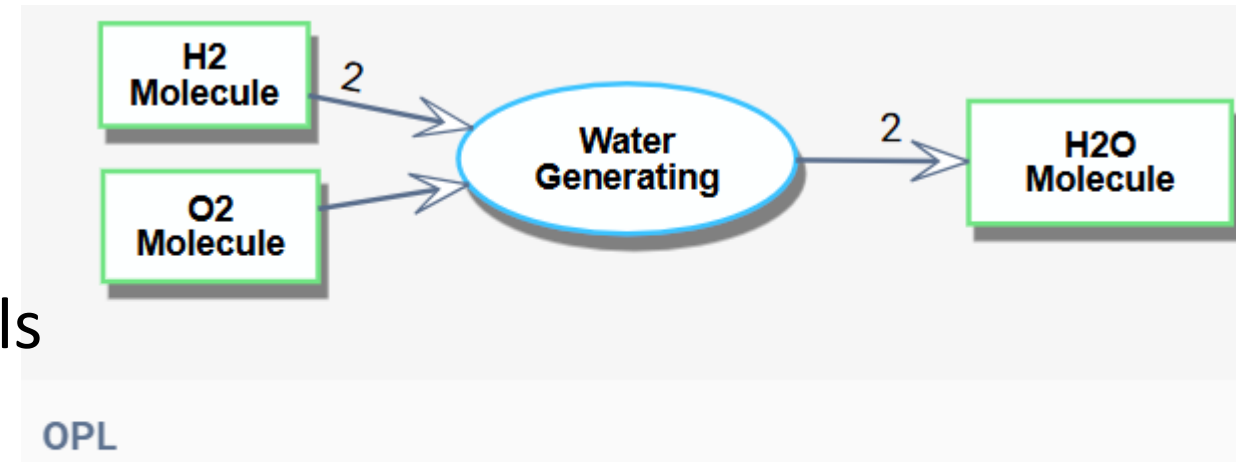
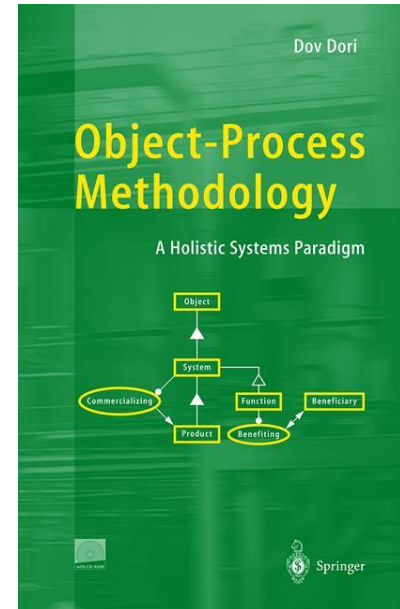
a formal model, in which every significant entity in the real world corresponds to a thing (object or process) in the model and relations among these things.

The challenge: Transforming knowledge expressed in natural language to a formal conceptual model

Object-Process Methodology (OPM)

ISO 19450:2024

- **Object:** a thing that exists
- **Process:** a thing that transforms one or more objects
- **Thing:** process or object
- **Bimodality:** everything is expressed in both graphics (OPD) and text (OPL)
- **Abstraction-refinement:** traversing levels of detail (in-zooming, unfolding) while
- **Integrating structure and behavior** in a single diagram kind.



OPL

Water Generating consumes 2 H2 Molecules and O2 Molecule.
Water Generating yields 2 H2O Molecules.

Object-Process Methodology (OPM) ISO 19450:2024



Online Browsing Platform (OBP)

Search

ISO 19450:2024(en) ×

ISO 19450:2024(en) Automation systems and integration — Object-Process Methodology

Table of contents

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Introduction

1 Scope

2 Normative references

3 Terms and definitions

4 Symbols

5 Conformance

6 Object-Process Methodology (OPM)

6.1 OPM modelling principles

6.2 OPM fundamental concepts

Introduction

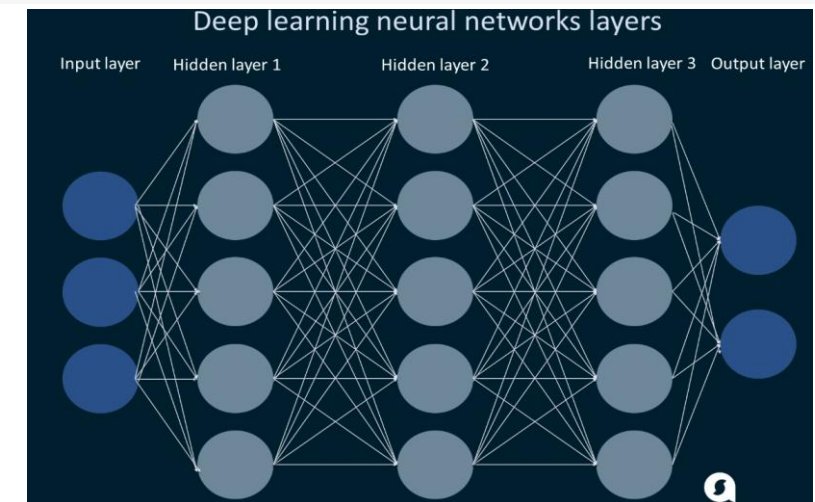
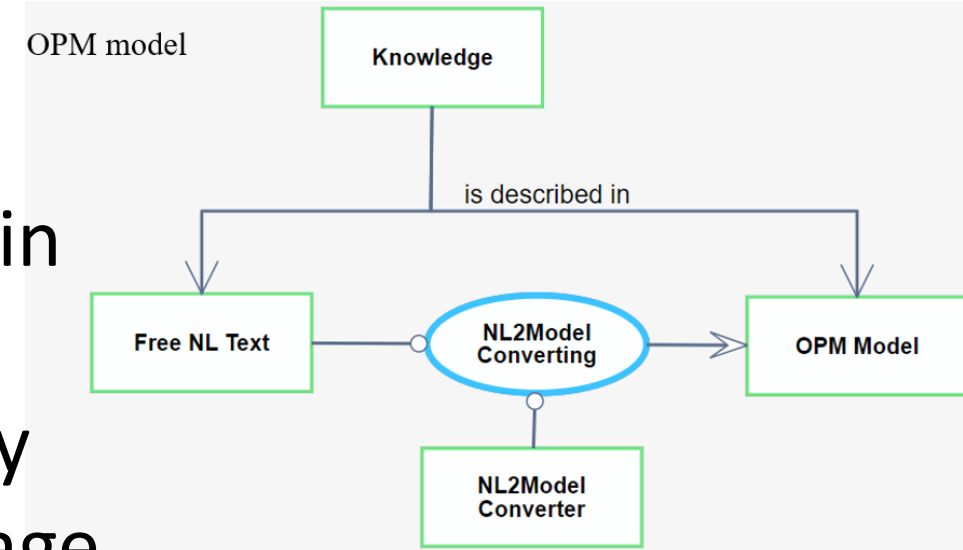
Object-Process Methodology (OPM) is a compact conceptual approach, language, and methodology for modelling and representation of automation systems. The application of OPM ranges from simple assemblies of elemental components to multidisciplinary, dynamic systems. OPM is suitable for implementation and support by tools using information and communication technology. This document specifies both the language and methodology aspects of OPM in order to establish a common system architecture, designers, and OPM-compliant tool developers to model all kinds of systems.

OPM provides two semantically equivalent modalities of representation for the same model: graphical and textual. A structured, interrelated Object-Process-Diagram (OPD) constitutes the graphical model, and a set of automatically generated sentences in a subset of the English language constitutes the textual model expressed in the Object-Process Language.

The Neuro-Conceptual AI Approach

A specialization of the **neuro-symbolic AI approach** for generating conceptual models in **Object-Process Methodology (OPM)** ISO 19450:2024, directly **from NL text** using large language models (**LLMs**) to enhance explainability and modeling automation

Xin Kang, Veronika Shteingardt, Yuhan Wang, and Dov Dori, **Neuro-Conceptual Artificial Intelligence: Integrating OPM with Deep Learning to Enhance Question Answering Quality**. *COLING 2025*



LLM and OPM complement each other

Attribute	Model	Attribute value	
		LLM	OPM
Automation Level		high (no human intervention after fine-tuning)	low (human professionals build the models)
Interpretability		low (inability to explain the result, conclusion, or recommendation)	high (built-in causality of how processes transform objects)
Causality-based querying ability		low (inability to query for causality)	high (via graph databases; Medvedev et al., 2021)
Underlying paradigm		neural networks, statistics	universal object-process ontology
Required preparation		model pretraining & fine-tuning	OPM model generation
Key applications		natural language processing (NLP) tasks: rephrasing, translation ...	MBSE; formal specification & communication of systems & phenomena
Output knowledge representation modality		textual : natural language; visual: images	visual : diagrammatic – OPDs; textual : plain English – OPL
Required input		natural language text	

The missing link: NL-to-Model Converting

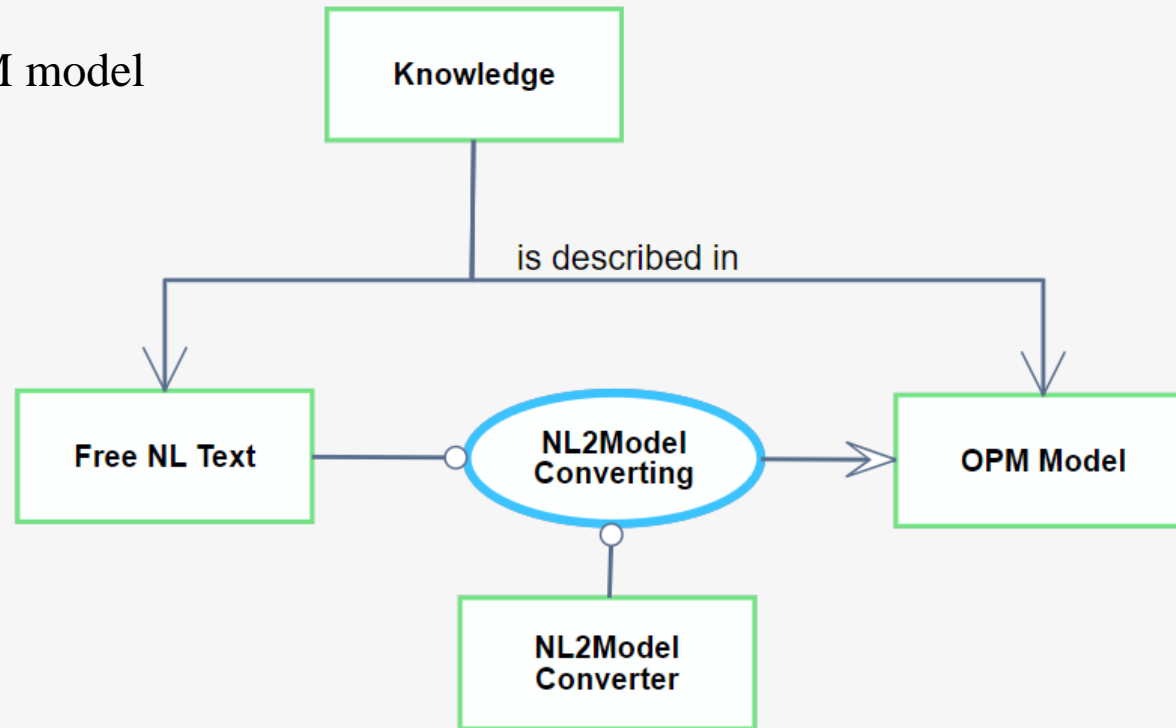
We wish to be able to automatically create a model of some knowledge or system specification/requirements directly from natural language (NL) text:

NL2OPM Converting OPM model

OPD: Object-Process Diagram - the visual modality

OPL: Object-process Language - the textual modality

OPL



Knowledge is described in Free NL Text and OPM Model.

NL2Model Converting requires Free NL Text and NL2Model Converter.

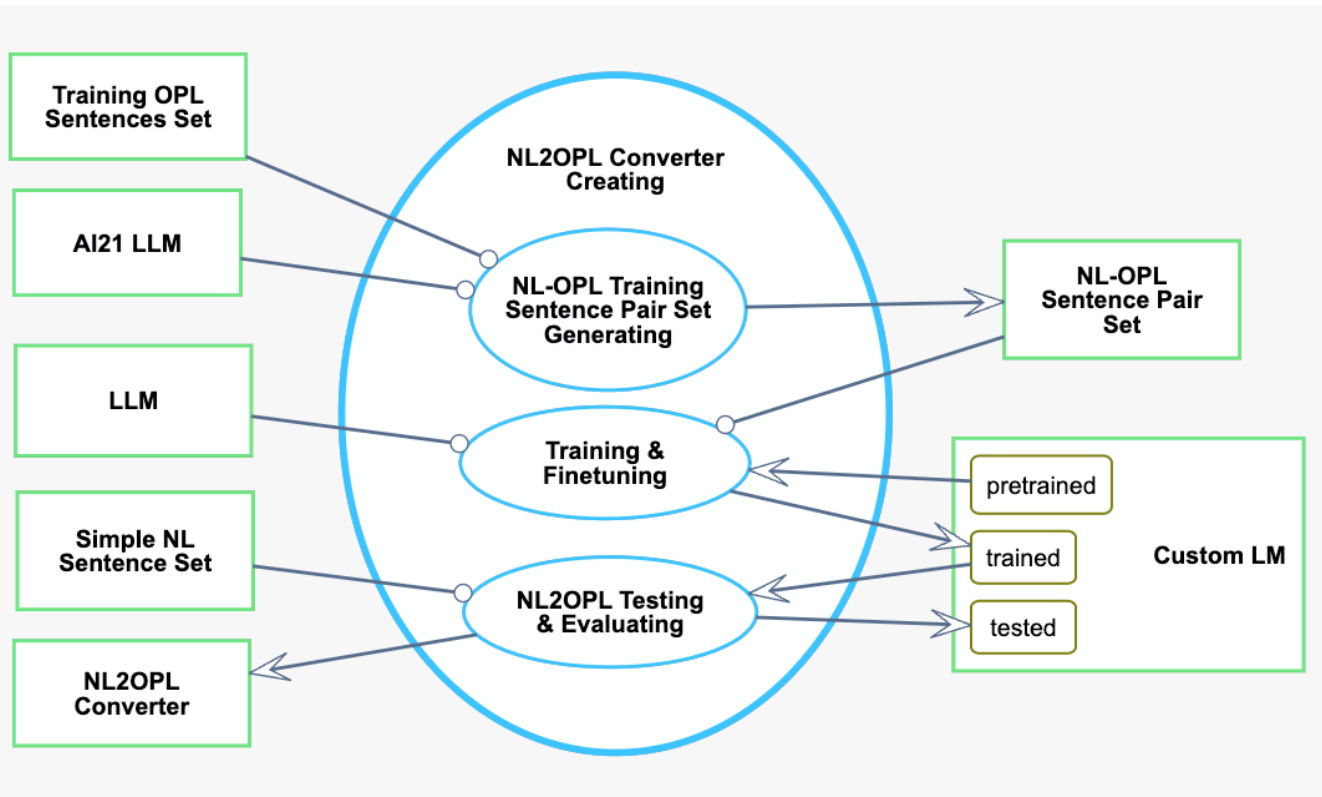
NL2Model Converting yields OPM Model.

Our High-level Research Goal:

Converting NL text to an OPM model (via NL2Model)

Concrete first goal:

Developing and evaluating the **NL2OPL** NLP task



NL2OPL Converter Creating from SD1.1.1 zooms in SD1.1.1.1 into **NL-OPL Training Sentence Pair Set Generating, Training & Fine-tuning, and NL2OPL Testing & Evaluating**, which occur in that time sequence.
Custom LM can be **pretrained**, **tested** or **trained**.
NL-OPL Training Sentence Pair Set Generating requires **AI21 LLM** and **Training OPL Sentences Set**.
NL-OPL Training Sentence Pair Set Generating yields **NL-OPL Sentence Pair Set**.
Training & Fine-tuning changes **Custom LM** from **pretrained** to **trained**.
Training & Fine-tuning requires **LLM** and **NL-OPL Sentence Pair Set**.
NL2OPL Testing & Evaluating changes **Custom LM** from **trained** to **tested**.
NL2OPL Testing & Evaluating requires **Simple NL Sentence Set**.
NL2OPL Testing & Evaluating yields **NL2OPL Converter**.

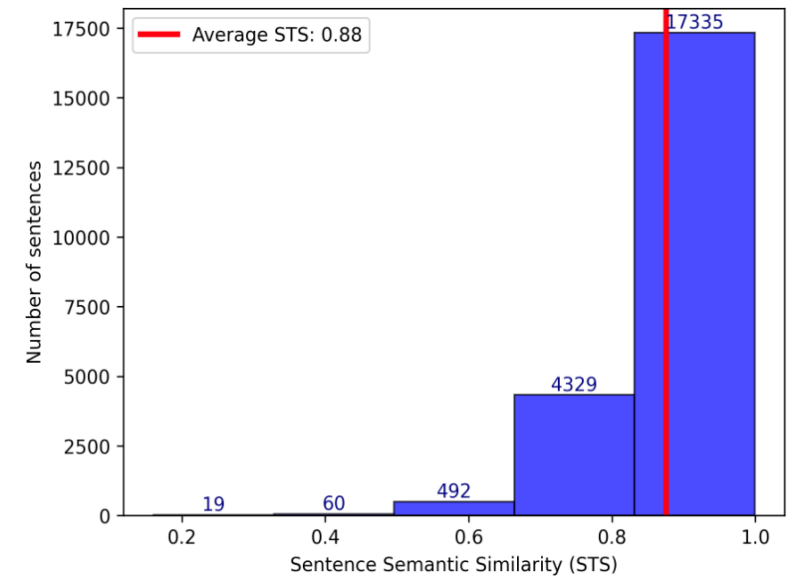


Training sentence pairs were obtained by paraphrasing

$(NL_1, OPL_1) = (\text{"As a result of Automatic Light Managing, the driver's vision becomes clearer as a result of automatic light management."}, \text{"**Automatic Light Managing of Automatic Light Managing System changes Vision of Driver from unclear to clear.**"})$, and

$(NL_2, OPL_2) = (\text{"With Automatic Light Managing System, the Vision of the Driver becomes clearer."}, \text{"**Automatic Light Managing of Automatic Light Managing System changes Vision of Driver from unclear to clear.**"})$.

This way we obtained 22,235 (NL, OPL) sentence pairs.



14 top-performing custom (fine-tuned) LMs

Model Name	Platform	Number of runs	Sentences category	SSTS	CS	OSXC	RTS
Custom LM 1	Google	24	round-trip	0.87	0.87	0.99	0.6
Custom LM 3	OpenAI	100	round-trip	0.81	0.82	0.99	0.52
Custom LM 11	OpenAI	100	round-trip	0.82	0.82	0.99	0.49
Custom LM 12	Google	15	round-trip	0.88	0.88	0.98	0.54
Custom LM 13	AI21	100	round-trip	0.87	0.87	0.98	0.58
Custom LM 14	Google	50	round-trip	0.88	0.88	0.98	0.53
Custom LM 5	AI21	100	round-trip	0.87	0.87	0.97	0.58
Custom LM 4	AI21	100	real-world	0.78	0.78	0.92	N/A
Custom LM 6	Google	10	real-world	0.80	0.80	0.91	N/A
Custom LM 2	Google	10	real-world	0.82	0.82	0.91	N/A
Custom LM 9	OpenAI	100	real-world	0.80	0.80	0.90	N/A
Custom LM 5	AI21	100	real-world	0.74	0.73	0.90	N/A
Custom LM 8	OpenAI	100	real-world	0.80	0.80	0.90	N/A
Custom LM 7	OpenAI	100	real-world	0.80	0.80	0.90	N/A
Custom LM 10	OpenAI	73	real-world	0.80	0.80	0.90	N/A

Round-trip sentence pair examples and scores

(OPL, NL) Sentence Pair		NL2OPL output	<i>OSXC</i>	<i>S</i>	<i>RTS</i>	<i>CS</i>
Input OPL Sentence	NL Sentence	Sentence				
OnStar System consists of Cellular Network, GPS, OnStar Console and VCIM - Vehicle Comm & interface Module.	The OnStar System is made up of the Cellular Network, GPS, OnStar Console, and VCIM - Vehicle Communications and Interfacing Module.	OnStar System consists of Cellular Network, GPS, OnStar Console and VCIM - Vehicle Comm & interface Module.	TRUE	0.94	TRUE	0.94
Driver communicates via OnStar Console.	OnStar Console is used by the driver to communicate.	Driver handles OnStar Console Communicating.	TRUE	0.87	FALSE	0.87
OnStar Advisor handles Driver Rescuing.	The OnStar Advisor is in charge of driver rescue.	OnStar Advisor handles Driver Rescuing.	TRUE	0.91	TRUE	0.91
Driver Rescuing requires OnStar System.	It is necessary to have OnStar in order to perform Driver Rescuing.	Driver Rescuing requires OnStar System.	TRUE	0.91	TRUE	0.91
Driver Rescuing affects Driver.	Rescuing a driver has an effect on him.	Driver Rescuing affects Driver.	TRUE	0.77	TRUE	0.77
Driver exhibits Danger Status.	The driver demonstrates a Danger Status.	Driver Performing shows Danger Status.	FALSE	0.93	FALSE	0

NL sentence
pair
examples
and scores

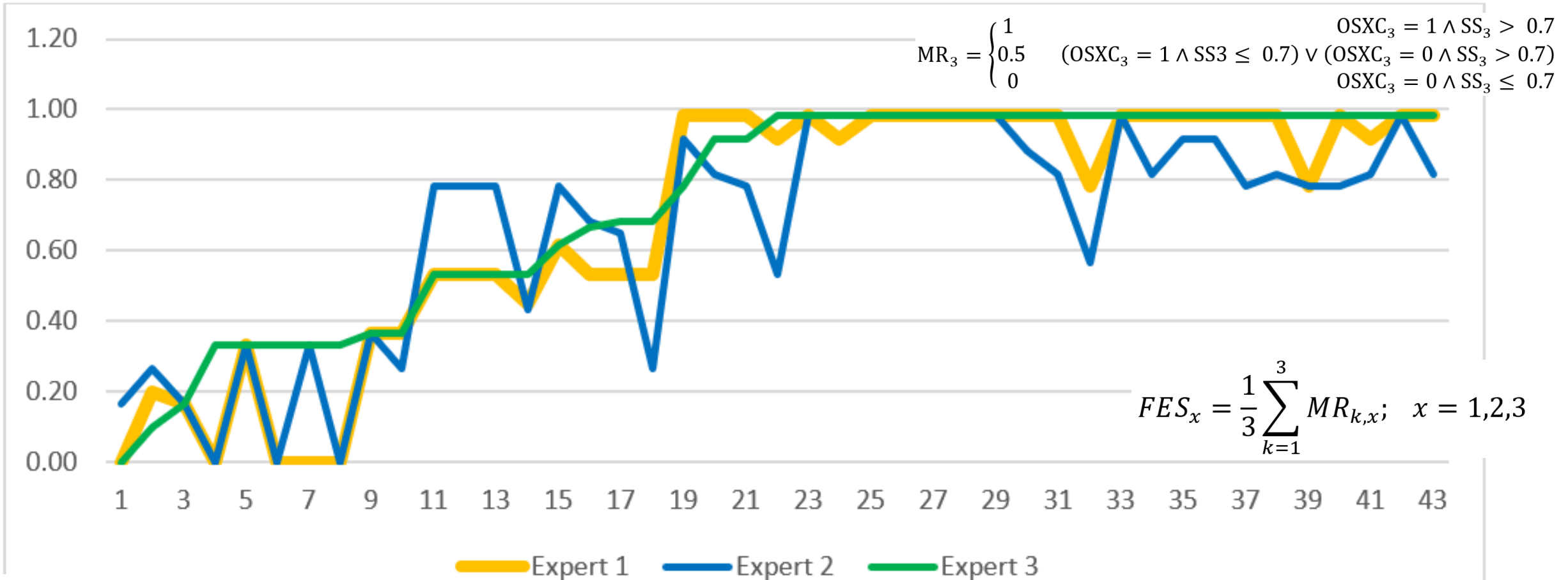
NL Sentence	NL2OPL output Sentence	OSXC	SSTS	CS
OnStar's in-vehicle information services use GPS satellite technology.	In-Vehicle Information Service of OnStar System uses GPS Satellite.	TRUE	0.93	0.93
Systems Engineering enables the successful realization of engineered systems.	Systems Engineering helps Achieved Engineered System.	FALSE	0.90	0
A product system delivers products.	Product System yields Product.	TRUE	0.76	0.76
OnStar links the vehicle and driver to the OnStar Center.	OnStar Service connects Driver and Vehicle to OnStar Center.	FALSE	0.94	0
The dispatcher identifies what emergency services are appropriate.	Dispatcher handles Emergency Service Assessing.	TRUE	0.88	0.88

Three human experts' evaluation scores of 43 (NL, OPL) sentence pairs

$$MR_1 = \begin{cases} 0 & OSXC * SS_1 < 0.7 \\ 1 & \text{otherwise} \end{cases}$$

$$MR_2 = OSXC * SS_2$$

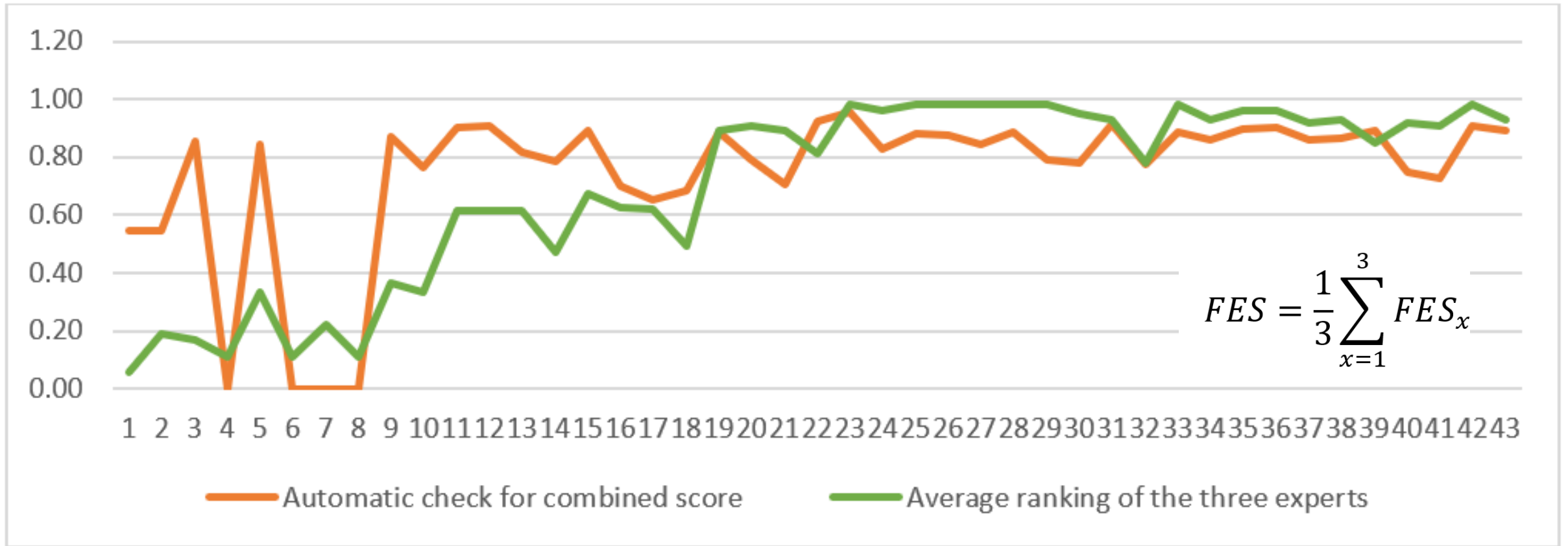
$$MR_3 = \begin{cases} 1 & OSXC_3 = 1 \wedge SS_3 > 0.7 \\ 0.5 & (OSXC_3 = 1 \wedge SS_3 \leq 0.7) \vee (OSXC_3 = 0 \wedge SS_3 > 0.7) \\ 0 & OSXC_3 = 0 \wedge SS_3 \leq 0.7 \end{cases}$$



$$FES_x = \frac{1}{3} \sum_{k=1}^3 MR_{k,x}; \quad x = 1,2,3$$

The inter-rated agreement was $\kappa = 0.845$;
 $\kappa > 0.8$ is considered “very high.”

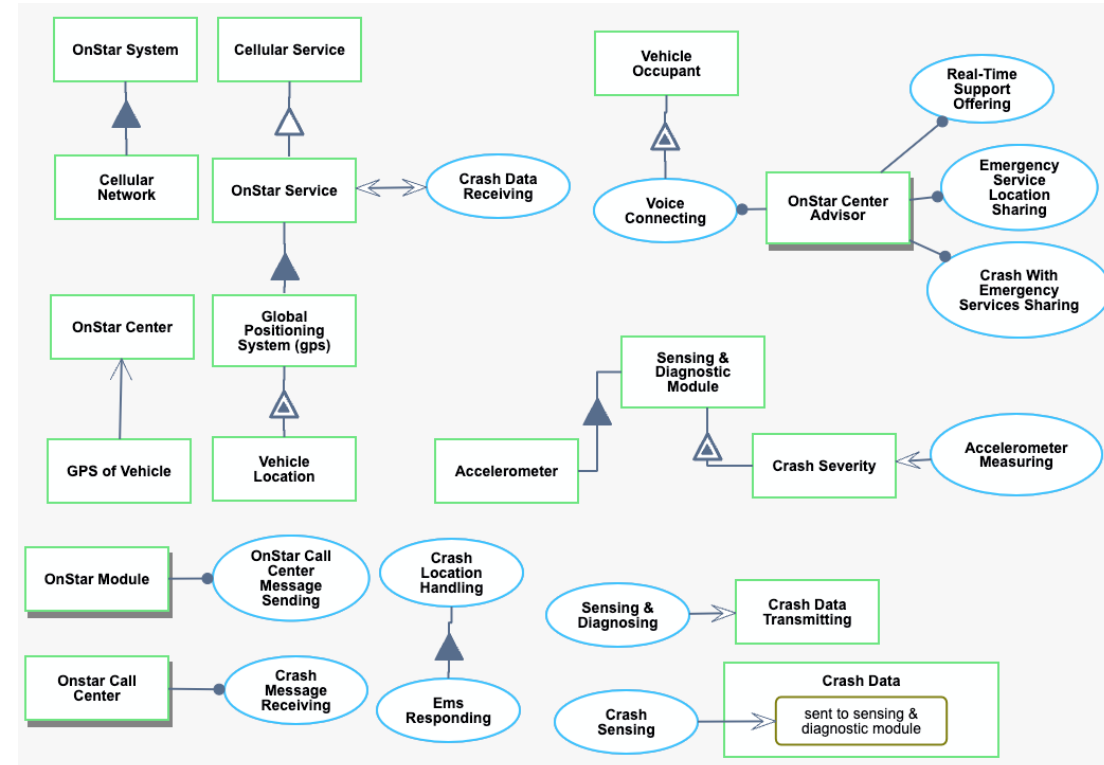
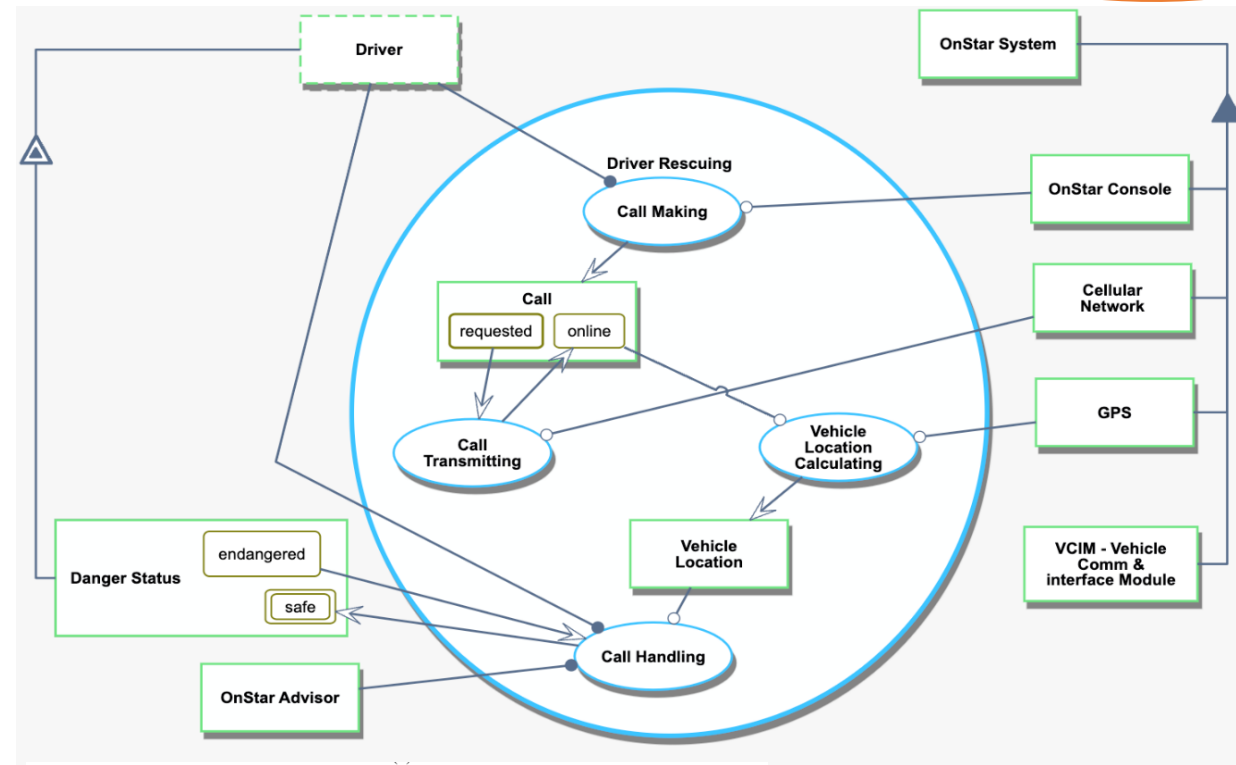
Automatic vs. average expert ranking



Automatic
vs. average
expert
ranking

Performance parameter	Custom LM 1 Round-trip sentences (N=58)	Custom LM 2 NL sentences (N=185)
OSXC – OPL syntax conformity	0.99 (STD 0.011)	0.92 (STD 0.016)
SSTS – Sentence semantic textual similarity	0.87 (STD 0.002)	0.82 (STD 0.004)
RTS – Round-trip score	0.63 (STD 0.02)	N/A
CS – Combined Score > 0.7, OSXC=1, and SSTS > 0.7	0.98 (STD 0.0001)	0.83 (STD 0.0002)

Human (left) vs. automatic model generation – both generated from the original text about OnStar System



Driver Rescuing from SD zooms in SD1 into Call Making, Vehicle Location Calculating, Call Transmitting, and Call Handling, which occur in that time sequence, as well as Call and Vehicle Location.

VCIM - Vehicle Comm & interface Module is a physical object.

Danger Status of Driver can be endangered or safe.

State safe is final.

Call can be online or requested.

State requested is initial.

OnStar System consists of Cellular Network, GPS, OnStar Console, a

Comm & interface Module.

Driver exhibits Danger Status.

Driver handles Call Making.

Call Making requires OnStar Console.

Call Making yields Call.

Call Transmitting changes Call from requested to online.

Call Transmitting requires Cellular Network.

Vehicle Location Calculating requires GPS and Call at state online.

Vehicle Location Calculating yields Vehicle Location.

Call Handling changes Danger Status of Driver from endangered to safe.

Driver and OnStar Advisor handle Call Handling.

Call Handling requires Vehicle Location.

OnStar Center Advisor is a physical object.

Crash Data is sent to sensing & diagnostic module.

Sensing & Diagnostic Module is a physical object.

OnStar Call Center is a physical object.

OnStar Service consists of Global Positioning System.

GPS of Vehicle relates to OnStar Center.

Sensing & Diagnostic Module consists of Accelerometer.

OnStar System consists of Cellular Network.

Vehicle Occupant exhibits Voice Connecting.

Sensing & Diagnostic Module exhibits Crash Severity.

Crash Location Handling consists of Ems Responding.

Global Positioning System exhibits Vehicle Location.

OnStar Center Advisor handles Real-Time Support Offering.

Accelerometer Measuring yields Crash Severity of Sensing & Diagnostic Module.

Crash Sensing yields Crash Data at state sent to sensing & diagnostic module.

Sensing & Diagnosing yields Crash Data Transmitting.

Crash Data Receiving affects OnStar Service.

OnStar Module handles OnStar Call Center Message Sending.

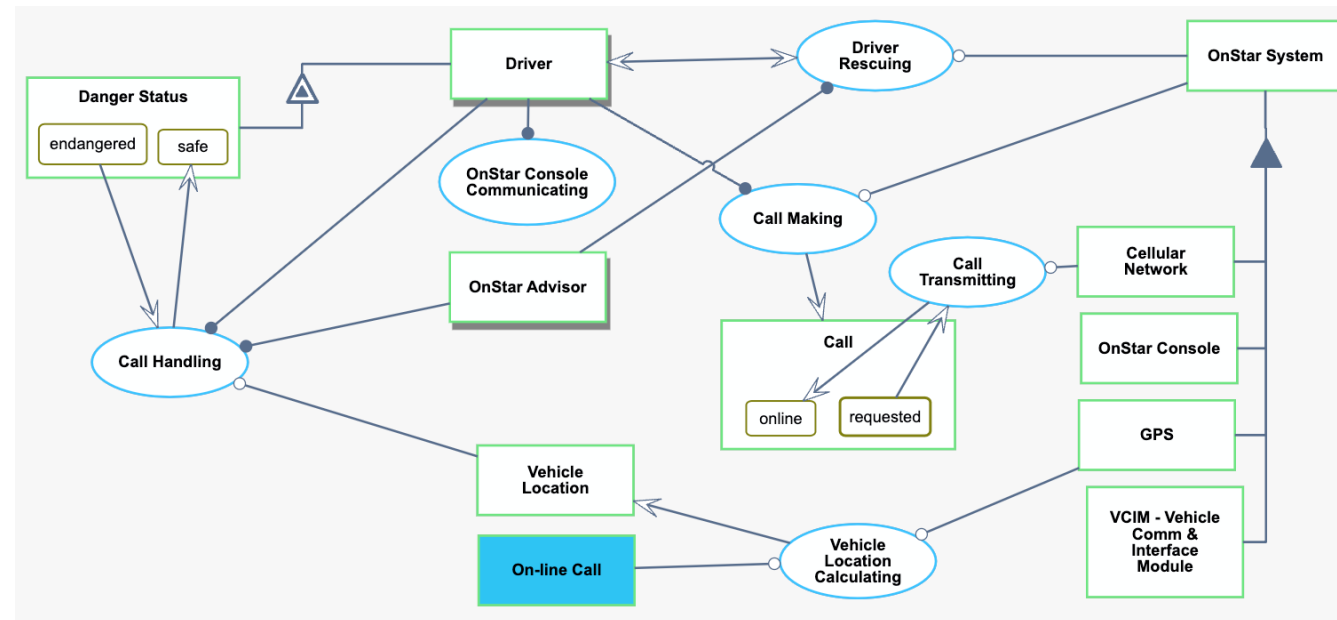
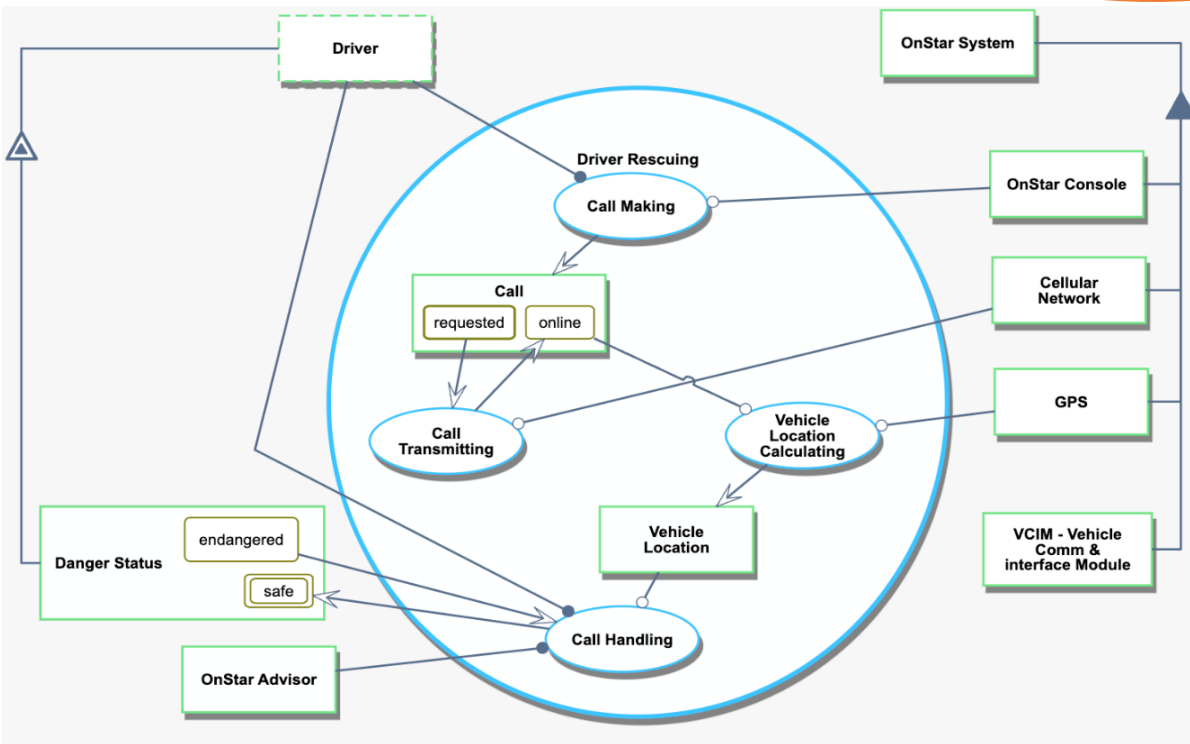
OnStar Call Center handles Crash Message Receiving.

OnStar Center Advisor handles Voice Connecting of Vehicle Occupant.

OnStar Center Advisor handles Emergency Service Location Sharing.

OnStar Center Advisor handles Crash With Emergency Services Sharing.

Human vs. automatic model generation – automatic model generated from paraphrased OPL of the human model



Driver is a physical object.
 OnStar Advisor is a physical object.
 Danger Status of Driver can be endangered or safe.
 Call can be online or requested.
 State requested is initial.
 OnStar System consists of Cellular Network, GPS, OnStar Console, and VCIM - Vehicle Comm & Interface Module.
 Driver exhibits Danger Status.
 Driver handles OnStar Console Communicating.
 OnStar Advisor handles Driver Rescuing.
 Driver Rescuing requires OnStar System.
 Driver Rescuing affects Driver.
 Driver handles Call Making.

Call Making requires OnStar System.
 Call Making yields Call.
 Call Transmitting changes Call from requested to online.
 Call Transmitting requires Cellular Network.
 Vehicle Location Calculating requires GPS and On-line Call.
 Vehicle Location Calculating yields Vehicle Location.
 Call Handling changes Danger Status of Driver from endangered to safe.
 Driver and OnStar Advisor handle Call Handling.
 Call Handling requires Vehicle Location.

Driver Rescuing from SD zooms in SD1 into Call Making, Vehicle Location Calculating, Call Transmitting, and Call Handling, which occur in that time sequence, as well as Call and Vehicle Location.

VCIM - Vehicle Comm & interface Module is a physical object.
 Danger Status of Driver can be endangered or safe.
 State safe is final.

Call can be online or requested.
 State requested is initial.

OnStar System consists of Cellular Network, GPS, OnStar Console, and VCIM - Vehicle Comm & interface Module.
 Driver exhibits Danger Status.
 Driver handles Call Making.
 Call Making requires OnStar Console.
 Call Making yields Call.

Call Transmitting changes Call from requested to online.

Call Transmitting requires Cellular Network.
 Vehicle Location Calculating requires GPS and Call at state online.
 Vehicle Location Calculating yields Vehicle Location.
 Call Handling changes Danger Status of Driver from endangered to safe.
 Driver and OnStar Advisor handle Call Handling.
 Call Handling requires Vehicle Location.

NL Text 2 – Systems Engineering Processes – ISO 15288 International Standard (snippet)

6.1.1 Acquisition process

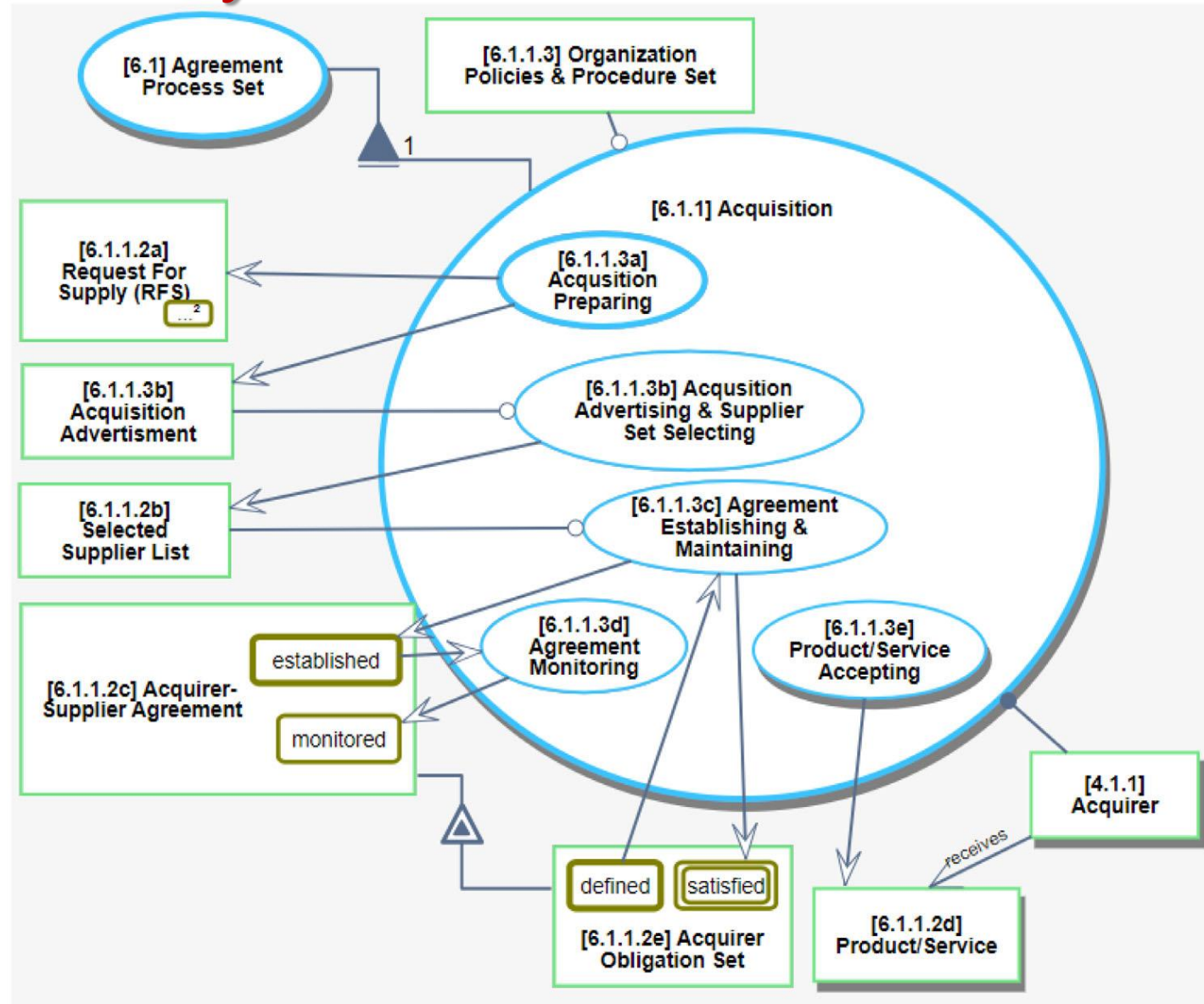
6.1.1.1 Purpose The purpose of the Acquisition process is to obtain a product or service in accordance with the acquirer's requirements. NOTE As part of this process, the agreement is modified when a change request is agreed to by both the acquirer and supplier.

6.1.1.2 Outcomes As a result of the successful implementation of the Acquisition process: a) A request for supply is prepared. b) One or more suppliers are selected. c) An agreement is established between the acquirer and supplier. d) A product or service complying with the agreement is accepted. e) Acquirer obligations defined in the agreement are satisfied.

6.1.1.3 Activities and tasks The acquirer shall implement the following activities and tasks in accordance with applicable organization policies and procedures with respect to the Acquisition process. a) Prepare for the acquisition. This activity consists of the following tasks: 1) Define a strategy for how the acquisition will be conducted. 2) Prepare a request for the supply of a product or service that includes the requirements. b) Advertise the acquisition and select the supplier. This activity consists of the following tasks: 1) Communicate the request for the supply of a product or service to potential suppliers. 2) Select one or more suppliers. ...

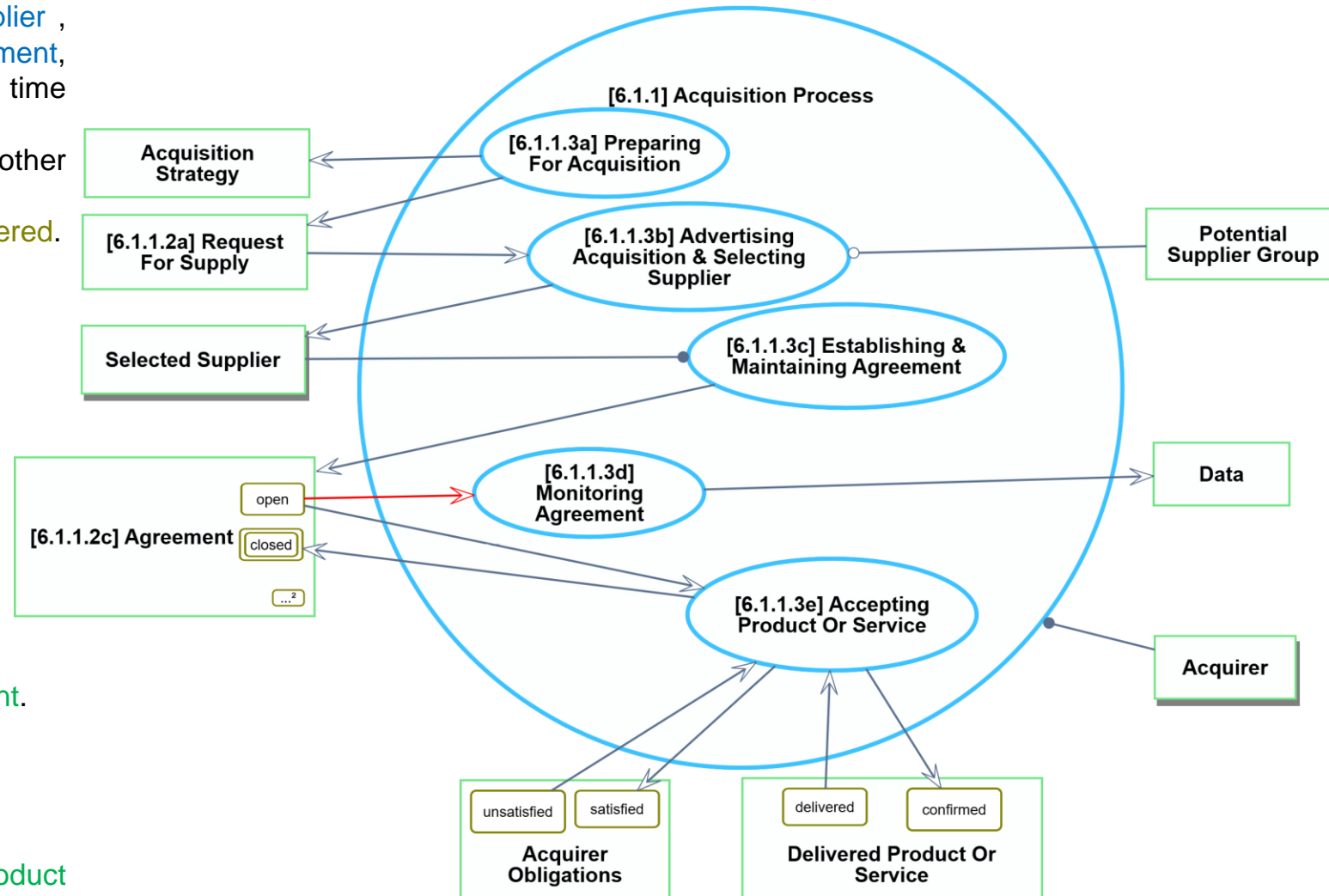
ISO 15288 – Manually built OPM model

1. Acquisition Process from SD zooms in SD1 into Acquisition Preparing, Acquisition Advertising & Supplier Set Selecting, Agreement Establishing & Maintaining, Agreement Monitoring, and Product/Service Accepting, which occur in that time sequence.
2. Agreement can be established or monitored. State established is initial.
3. Acquirer Obligation Set of Agreement can be defined or satisfied. State defined is initial. State satisfied is final.
4. Agreement exhibits Acquirer Obligation Set.
5. Acquirer receives Product/Service.
6. Acquirer handles Acquisition Process.
7. Acquisition Process requires Organization Policies & Procedure Set.
8. Acquisition Preparing yields Request For Supply and Acquisition Advertisement.
9. Acquisition Advertising & Supplier Set Selecting requires Acquisition Advertisement.
10. Acquisition Advertising & Supplier Set Selecting yields Selected Supplier List.
11. Agreement Establishing & Maintaining requires Selected Supplier List.
12. Agreement Establishing & Maintaining yields Agreement at state established.
13. Agreement Monitoring changes Agreement from established to monitored.
14. Product/Service Accepting changes Acquirer Obligation Set of Agreement from defined to satisfied.
15. Product/Service Accepting yields Product/Service.



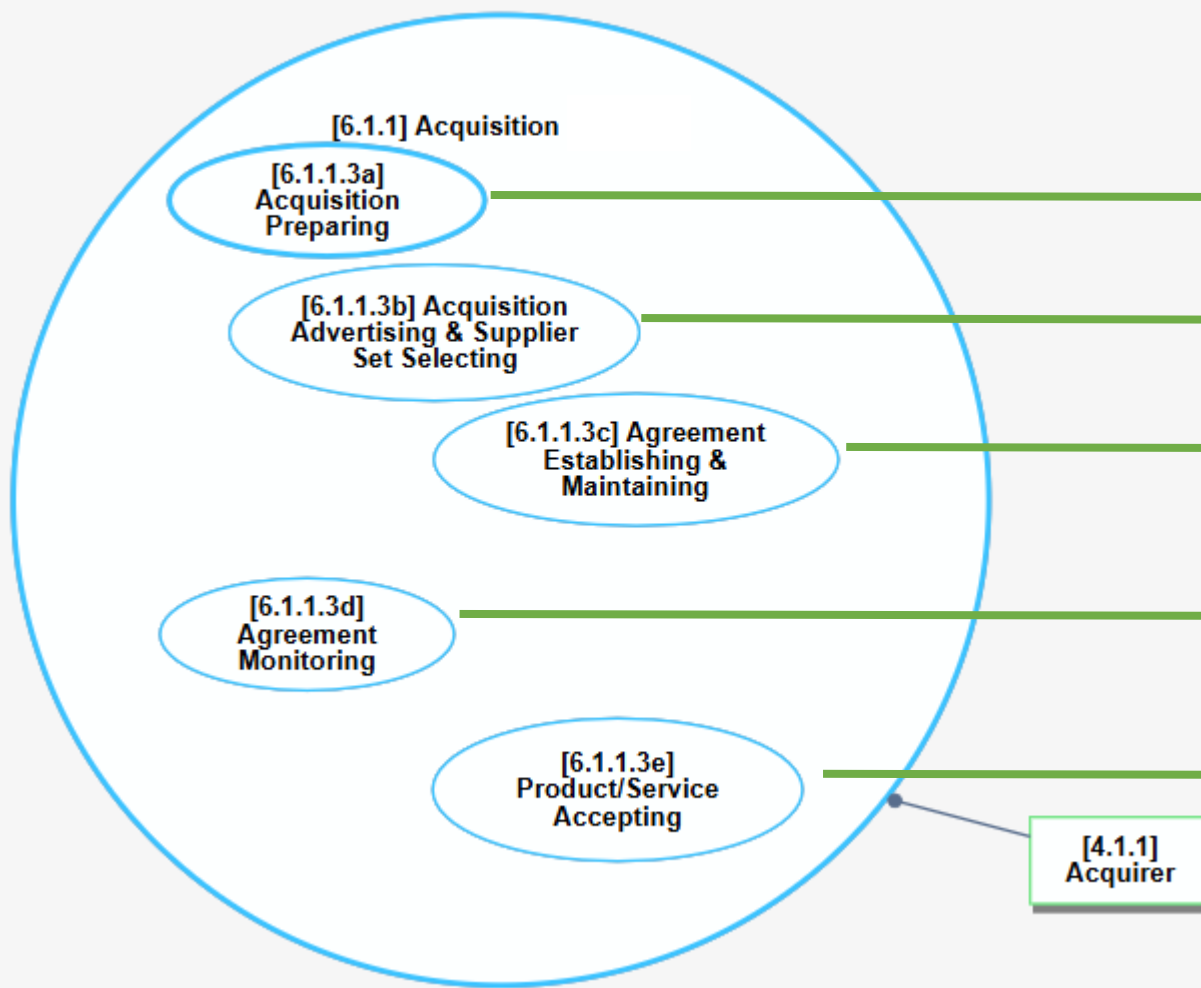
ISO 15288 – Automatically-generated model

1. Acquisition Process from SD zooms in SD1 into Preparing For Acquisition, Advertising Acquisition & Selecting Supplier, Establishing & Maintaining Agreement, Monitoring Agreement, and Accepting Product Or Service, which occur in that time sequence.
2. Agreement can be closed, open or at one of two other states. State closed is final.
3. Delivered Product Or Service can be confirmed or delivered.
4. Acquirer Obligations can be satisfied or unsatisfied.
5. Acquirer handles Acquisition Process.
6. Preparing For Acquisition yields Acquisition Strategy and Request For Supply.
7. Advertising Acquisition & Selecting Supplier requires Potential Supplier Group.
8. Advertising Acquisition & Selecting Supplier consumes Request For Supply.
9. Advertising Acquisition & Selecting Supplier yields Selected Supplier.
10. Selected Supplier handles Establishing & Maintaining Agreement.
11. Establishing & Maintaining Agreement yields Agreement.
12. Monitoring Agreement consumes Agreement.
13. Monitoring Agreement yields Data.
14. Accepting Product Or Service changes Agreement from open to closed.
15. Accepting Product Or Service changes Delivered Product Or Service from delivered to confirmed.
16. Accepting Product Or Service changes Acquirer Obligations from unsatisfied to satisfied.

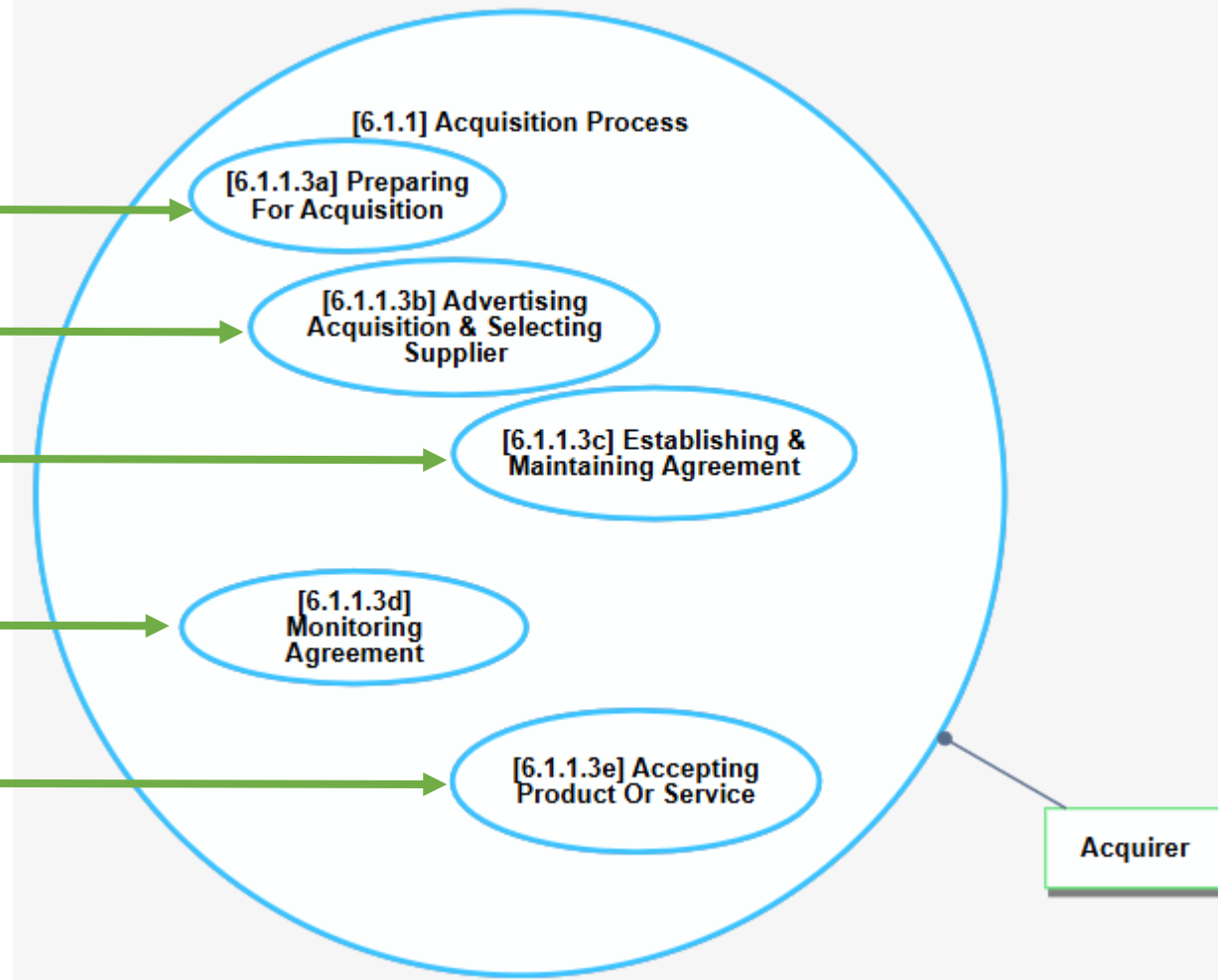


ISO 15288 model comparison: Processes

Manually built OPM model

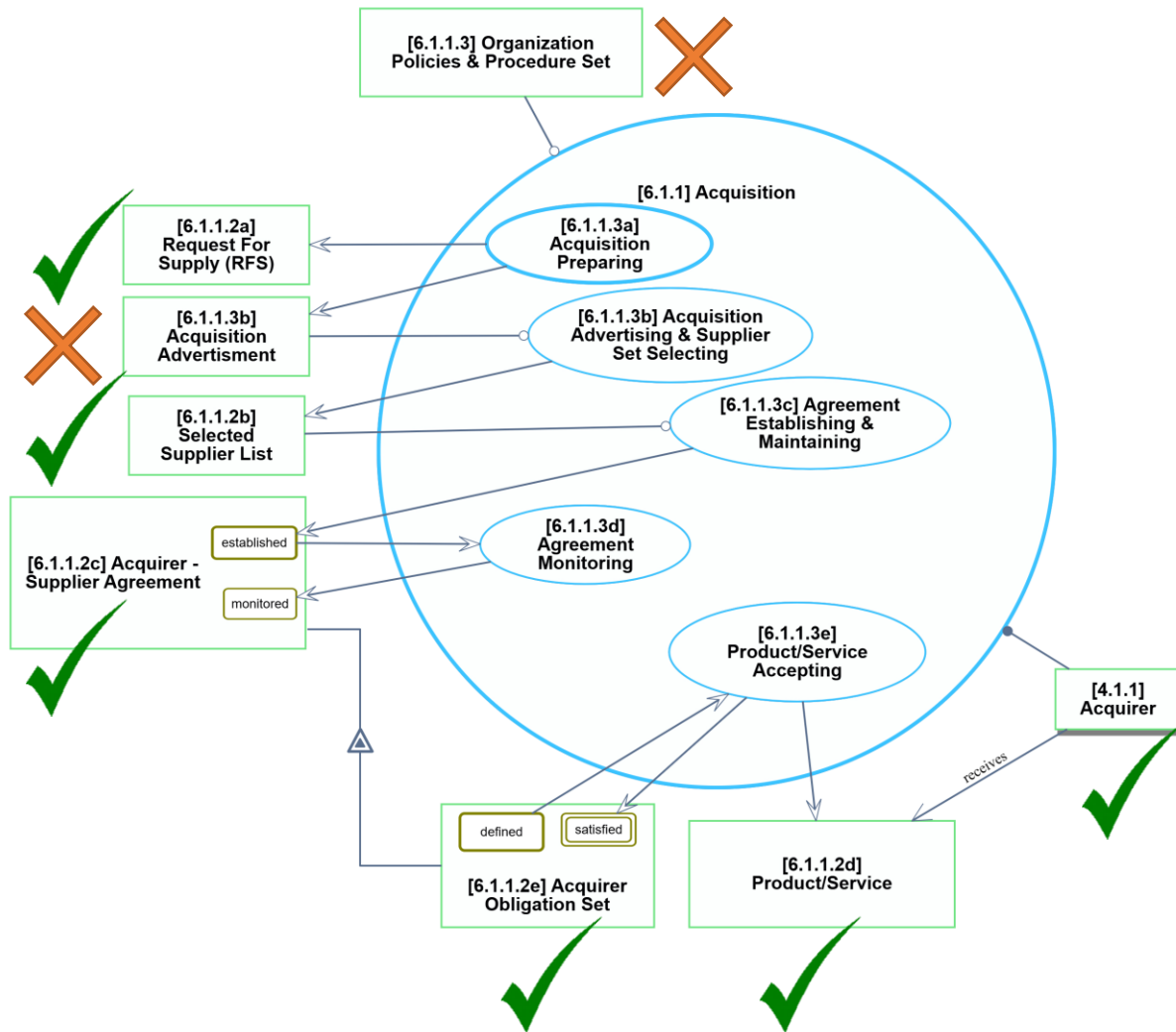


NL2OPM-generated model

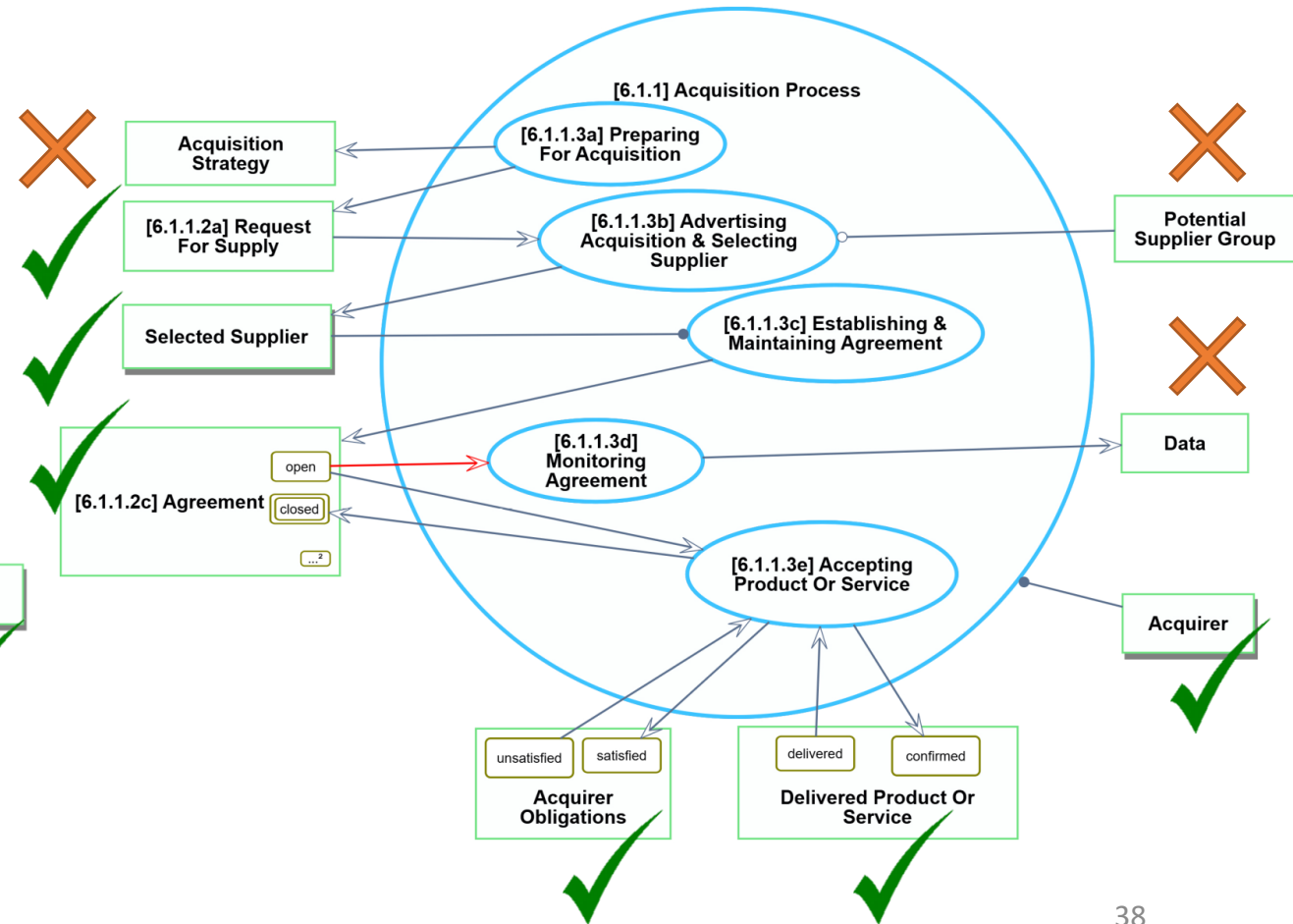


ISO 15288 model comparison: Objects

Manually built OPM model



NL2OPM-generated model



ISO 15288 – OPL sentence comparison

Manually built OPM model

NL2OPM-generated model

Acquirer handles Acquisition.

Acquirer handles Acquisition Process.

Acquisition requires Organization Policies & Procedure Set.

X

Acquirer receives Product/Service.

X (We did not train to use “tags”)

Agreement can be established or monitored. State established is initial.

States statement is missing

Agreement exhibits Acquirer Obligation Set.

X

Acquirer Obligation Set of Agreement can be defined or satisfied. State defined is initial. State satisfied is final.

Acquirer Obligations can be satisfied or unsatisfied.

Agreement Establishing & Maintaining requires Selected Supplier List.

Selected Supplier handles Establishing & Maintaining Agreement.

Acquisition Preparing yields Request For Supply and Acquisition Advertisement.

Preparing For Acquisition yields Acquisition Strategy and Request For Supply.

X

Advertising Acquisition & Selecting Supplier consumes Request For Supply.

Acquisition Advertising & Supplier Set Selecting requires Acquisition Advertisement.

Advertising Acquisition & Selecting Supplier requires Potential Supplier Group.

Acquisition Advertising & Supplier Set Selecting yields Selected Supplier List.

Advertising Acquisition & Selecting Supplier yields Selected Supplier.

Agreement Establishing & Maintaining yields Agreement at state established.

Establishing & Maintaining Agreement yields Agreement.

Agreement Monitoring changes Agreement from established to monitored.

Monitoring Agreement consumes Agreement. Monitoring Agreement yields Data.

Product/Service Accepting changes Acquirer Obligation Set of Agreement from defined to satisfied.

Accepting Product Or Service changes Acquirer Obligations from unsatisfied to satisfied.

Product/Service Accepting yields Product/Service.

Accepting Product Or Service changes Delivered Product Or Service from delivered to confirmed.

X

Accepting Product Or Service changes Agreement from closed to open.

Acquisition from SD zooms in SD1 into Acquisition Preparing, Acquisition Advertising & Supplier Set Selecting, Agreement Establishing & Maintaining, Agreement Monitoring, and Product/Service Accepting, which occur in that time sequence.

[6.1.1] Acquisition Process zooms into [6.1.1.3a] Preparing for Acquisition, [6.1.1.3b] Advertising Acquisition and Selecting Supplier, [6.1.1.3c] Establishing and Maintaining Agreement, [6.1.1.3d] Monitoring Agreement, and [6.1.1.3e] Accepting Product or Service, which occur in that time sequence.

NL2OPL evaluation results

Metric	NL Text 1: OnStar	NL Text 2: ISO 15288	Average
Elements generation score	0.75	0.73	0.74
OPL syntax score	0.93	0.96	0.95

NL2OPL typical problems

- ❖ NL2OPL **invents** entities
- ❖ NL2OPL **ignores** some information
- ❖ NL2OPL can sometimes **deviate** from the OPL **semantics and naming rules**
- ❖ NL2OPL **changes the names** of entities to their **synonymous**

- ❖ Some OPM entities and links are better represented in the NL2OPL generated model, specifically
 - ❖ processes
 - ❖ object states
 - ❖ state transitions

- ❖ NL2OPL has difficulty “understanding” some OPM relations, specifically
 - ❖ consumption link
 - ❖ instrument link

NL2OPL advantages

- ❖ **Accelerating the modeling process** by offering an initial model
- ❖ **Suggesting** possible missing entities
- ❖ **Highlighting inconsistencies** in the NL text
- ❖ **Identifying ambiguities** in the NL text

NL2OPL Limitations

- ❖ Does not support the automatic generation of complex multiple-level models
 - ❖ needs to improve abstraction-refinement capability
- ❖ Requires manual model verification
- ❖ OPM naming conventions and OPL syntax not always followed
- ❖ Results may be different across LLMs and Prompts (expected)

Future Research

- **Performance by NL text class:** technical documents, manuals, patents, scientific papers, prose, poetry...
- **Performance by NL text complexity:** various sizes for the various NL text classes
- **OPD Set Hierarchy Support:** abstraction-refinement – develop automatic “systems thinking”
- **Direct visual modality generation:** Generation the hierarchically-organized OPD set directly from NL text



THANKYOU

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