

# Risk assessment with AILA: Automated and Intelligent Likelihood Assignment

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20th Workshop on Security Frameworks  
“Security Testing”

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UNIVERSITÀ  
degli STUDI  
di CATANIA



Radboud Universiteit Nijmegen

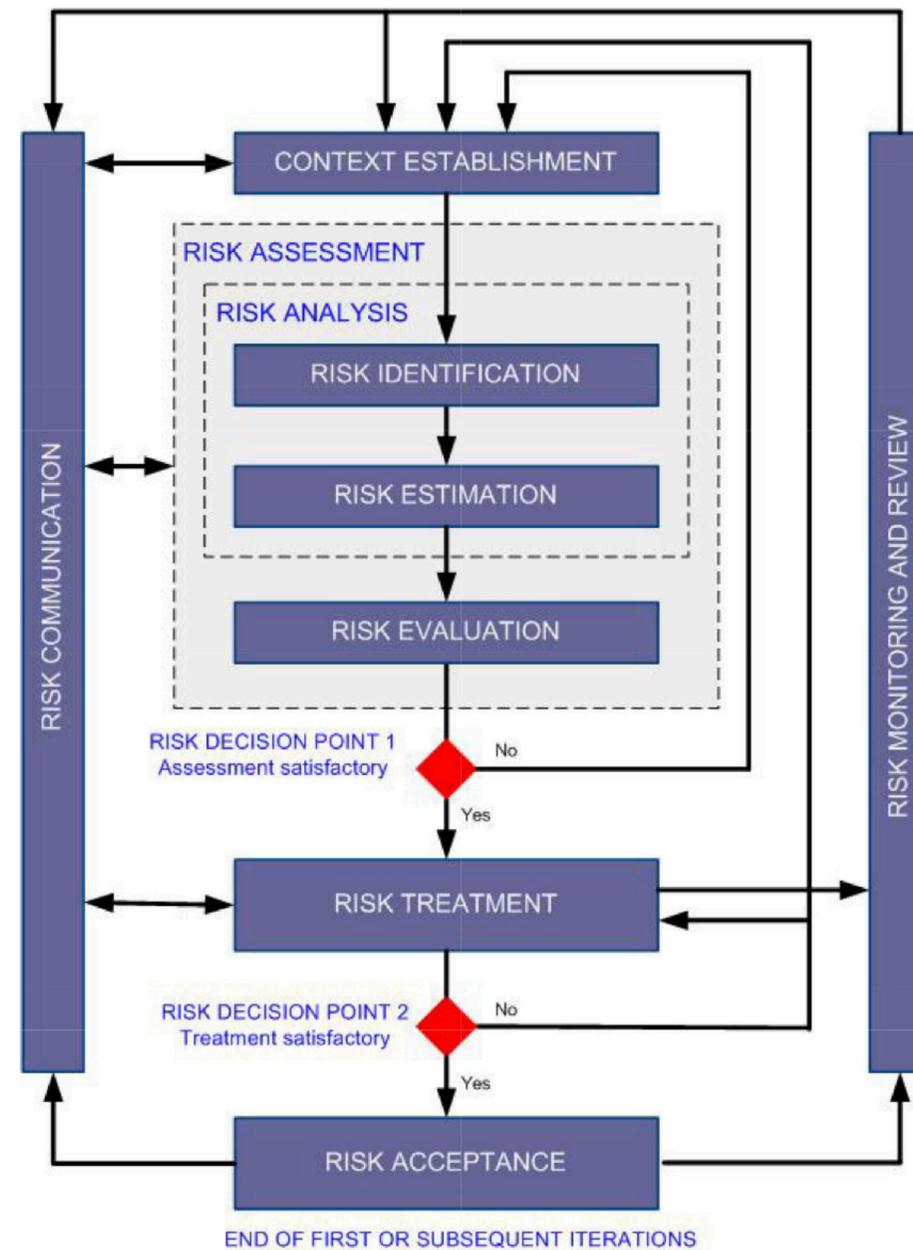


SCUOLA  
ALTI STUDI  
LUCCA

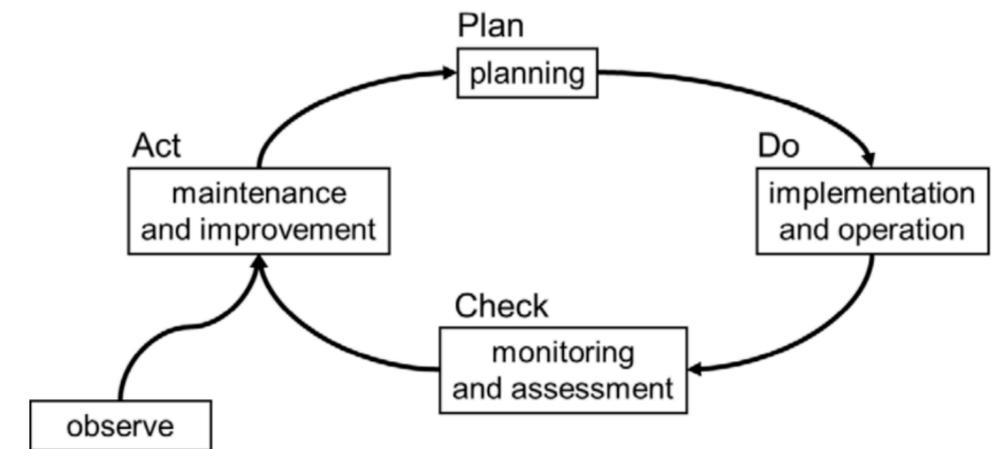
# Risk Management in a Nutshell



*“If you don't invest in risk management, it doesn't matter what business you're in, it's a risky business.” - Gary Cohn*



ISO 27005



ISMS PDCA Cycle [ISO 27001]

# Risk Assessment Concepts

## RA inputs:

- Assets
- Threats
- Safeguards

## RA outputs:

- Impact
- Risk

## Other factors:

- Security dimensions
- Likelihood

<i>Risk</i>		<i>Likelihood</i>				
		VL	L	M	H	VH
<i>Impact</i>	VH	H	VH	VH	VH	VH
	H	M	H	H	VH	VH
	M	L	M	M	H	H
	L	VL	L	L	M	M
	VL	VL	VL	VL	L	L

Risk for dummies  $R = L \times I$

Actual risk  $R = \dots?$

where R is the risk, L the likelihood and I the impact.

# Privacy Risks

A variety of **personal data** is collected by services to “improve” the user’s experience.

## OWASP Top 10 Privacy Risks

P1 - Web Application Vulnerabilities

P2 - Operator-sided Data Leakage

P3 - Insufficient Data Breach Response

P4 - Consent on Everything

**P5 - Non-transparent Policies, Terms and Conditions**

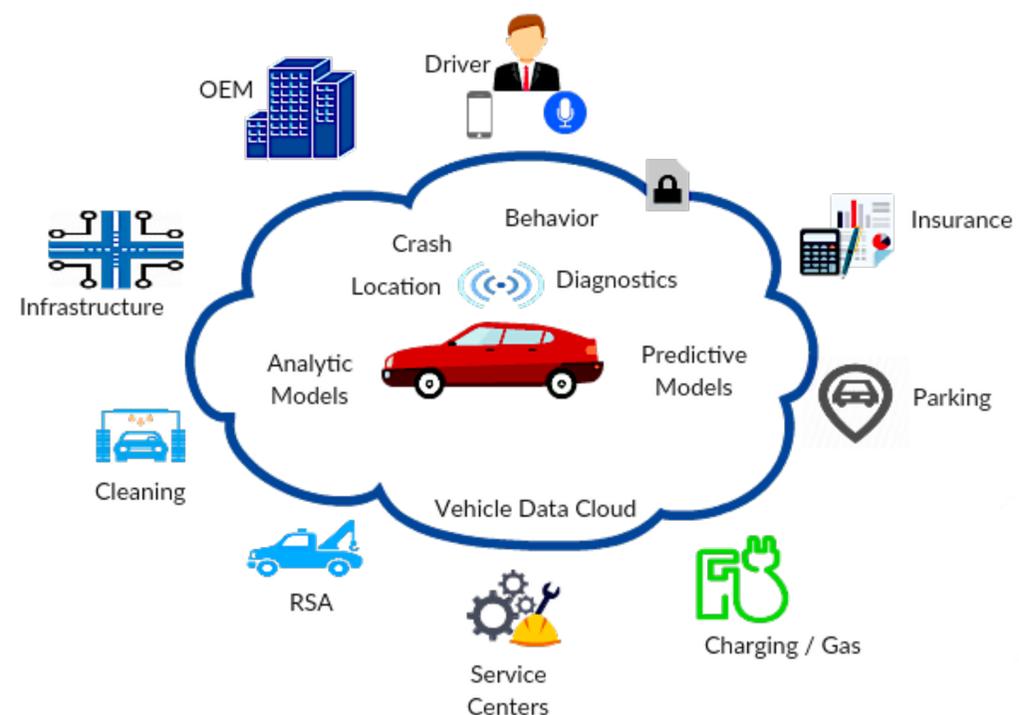
P6 - Insufficient Deletion of User Data

P7 - Insufficient Data Quality

P8 - Missing or Insufficient Session Expiration

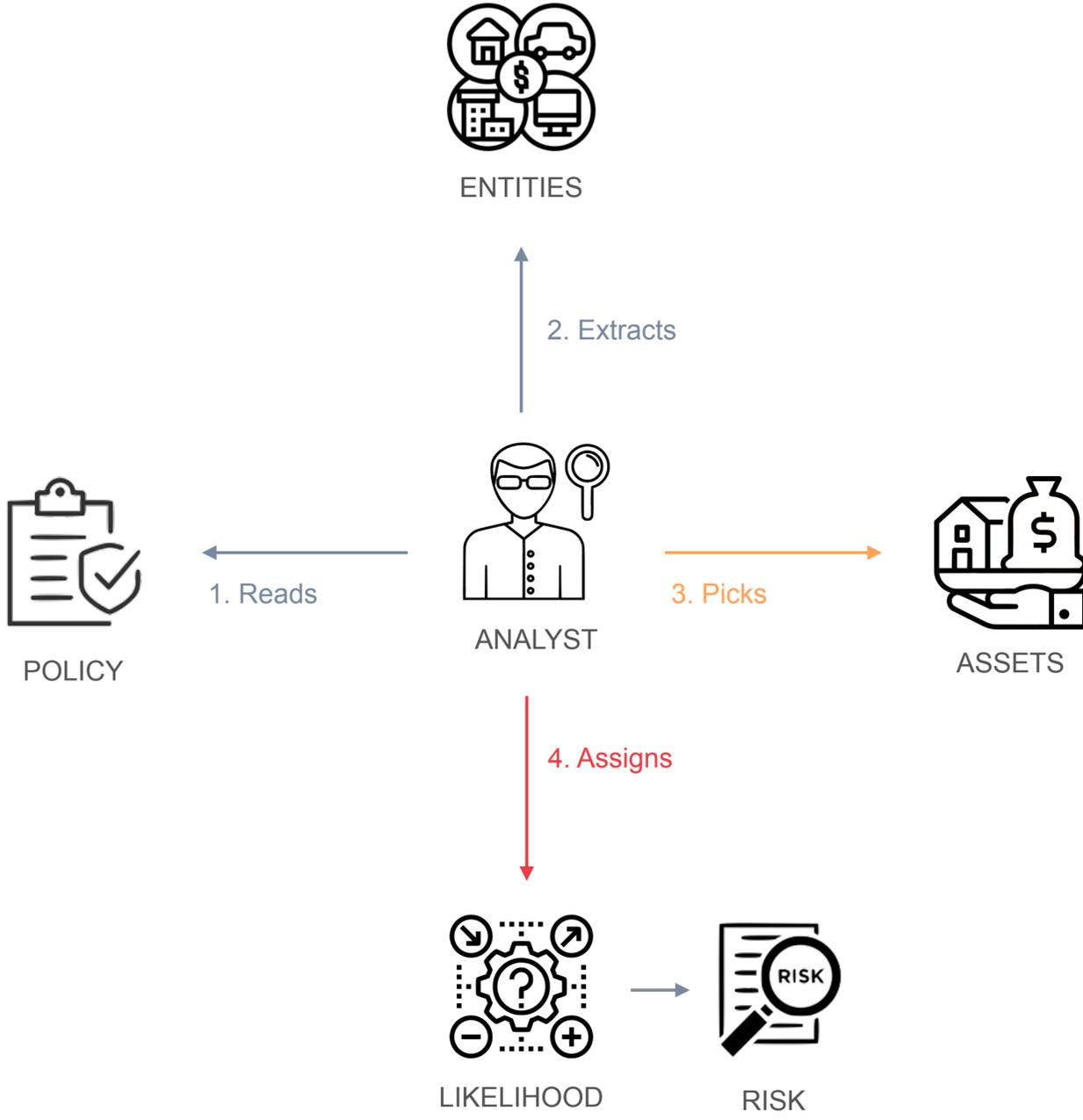
P9 - Inability of Users to Access and Modify Data

P10 - Collection of Data Not Required for the User-Consented Purpose



He's making a list  
He's checking it twice  
He's gonna find out who's naughty or nice  
Santa Claus is in contravention of the GDPR (EU) 2016/679

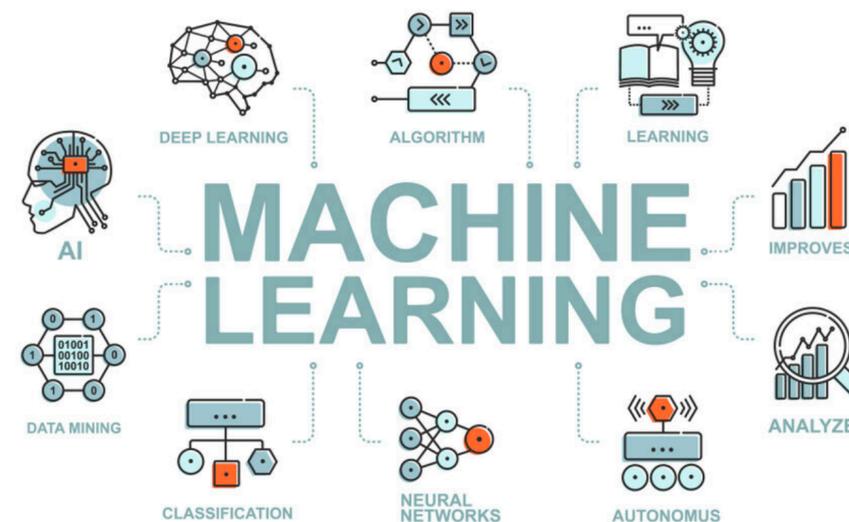
# Privacy Policy RA



# AILA - Automated and Intelligent Likelihood Assignment

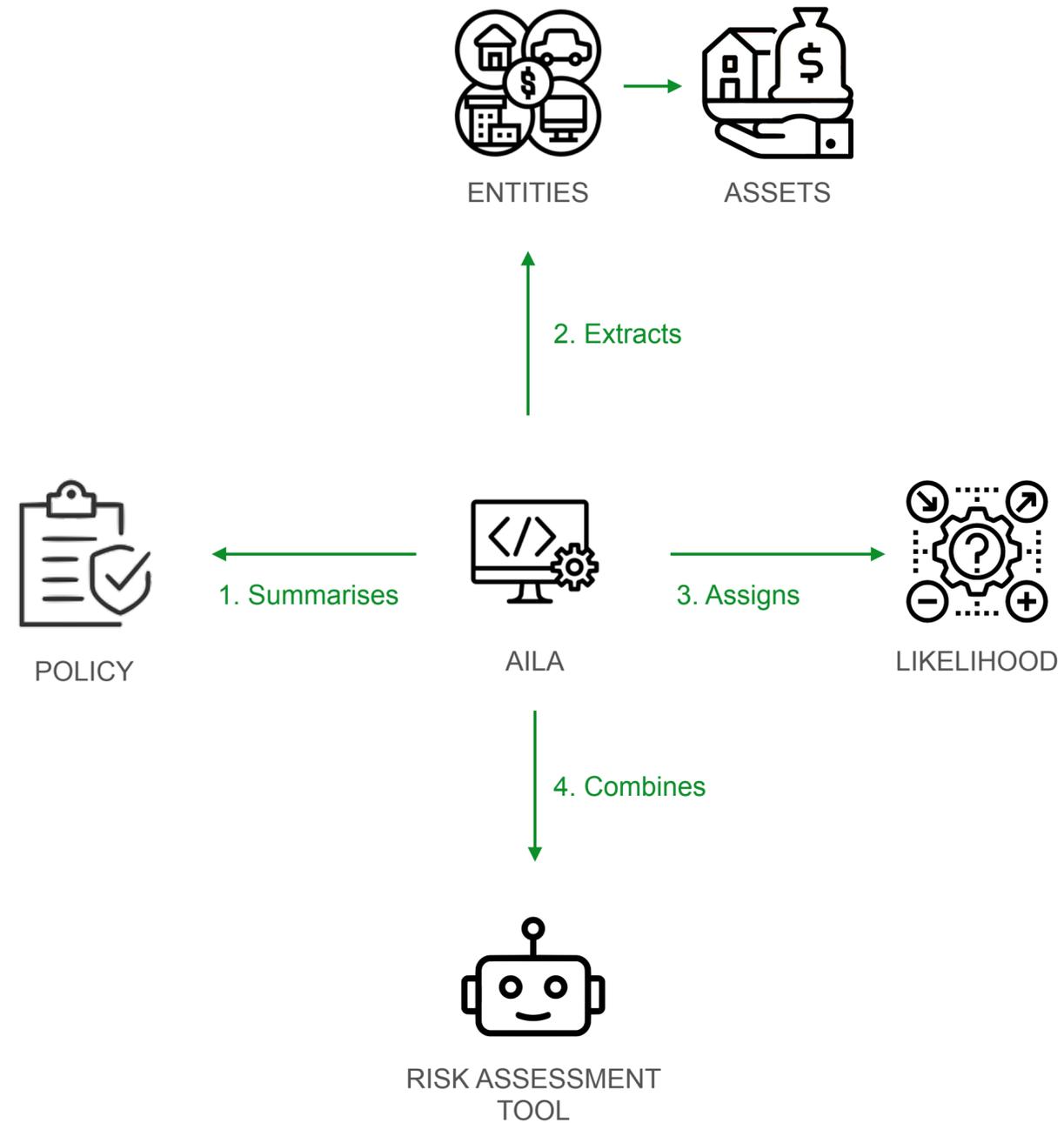
AILA aims at reducing the influence of **subjectivity** and **distraction**.

AILA uses *Natural Language Processing* and *Machine Learning*.



The process is also integrated with a *RA tool*.

# AILA in a Nutshell

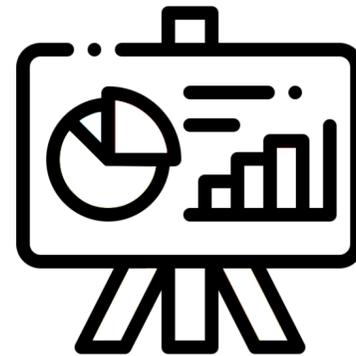


# AILA Methodology

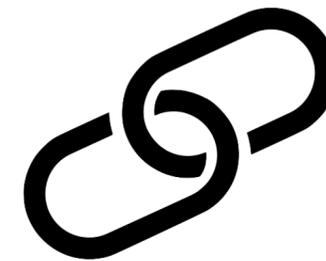
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1. AUTOMATED ASSET  
EXTRACTION



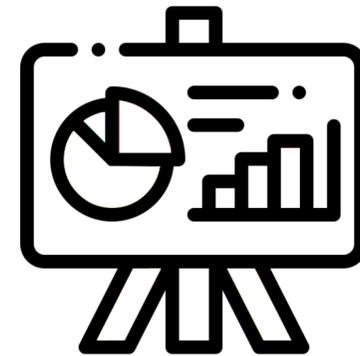
2. LIKELIHOOD  
DETERMINATION  
THROUGH AILA



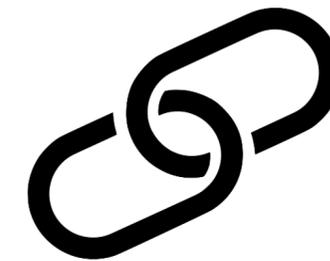
3. COMBINED  
LIKELIHOOD  
DETERMINATION

# AILA Methodology

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2. LIKELIHOOD  
DETERMINATION  
THROUGH AILA



3. COMBINED  
LIKELIHOOD  
DETERMINATION

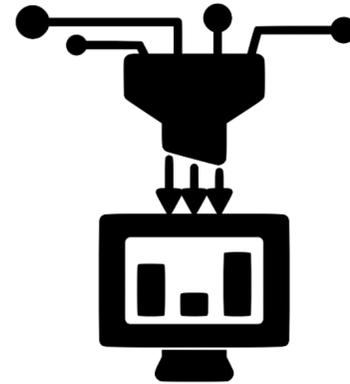
# 1. Automated Asset Extraction

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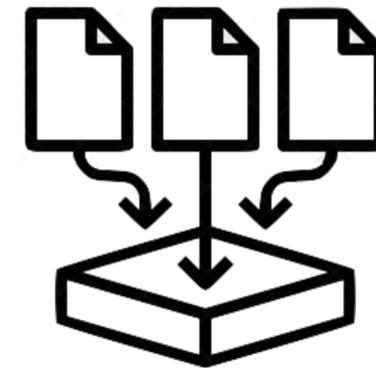
This step is carried out by the **AILA Entity Extractor (AILAEE)**.



SUMMARISATION  
USING N-GRAMS



ENTITY RECOGNITION  
ALGORITHM



COLLECTION OF  
POLICY SENTENCES

# 1. AILAE - Preprocessing

> Bigrams Identification



> Sentence Extraction



> Text Summarisation



> Entropy Measurement

*Is the loss of information negligible?* → **Shannon's Entropy**

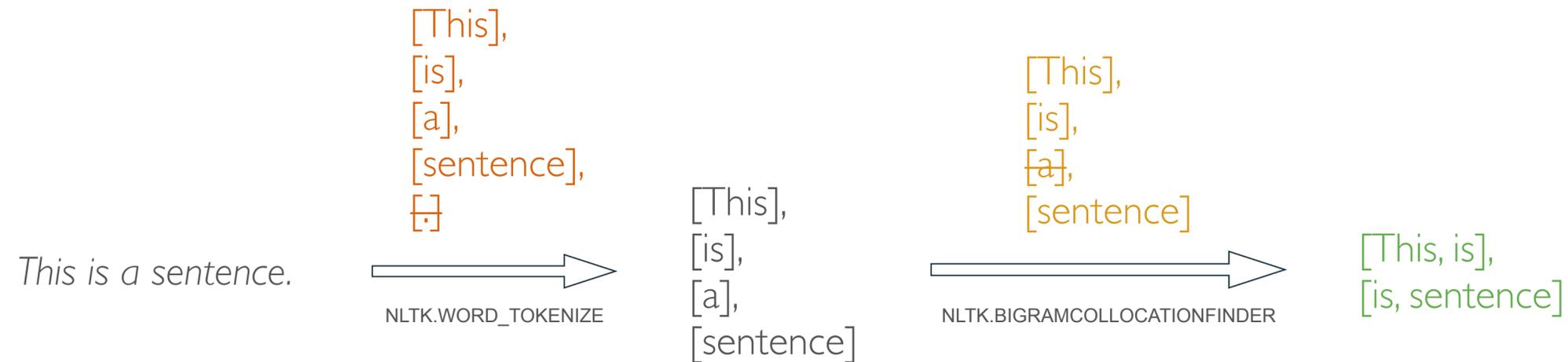


# 1. AILAE - Preprocessing

## > Bigrams Identification



The aim is to **remove irrelevant text** and only keep the most relevant components (*nouns, verbs, adjectives*).



# 1. AILAE - Preprocessing

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## > Sentence Extraction

Sentences containing **verbs** are the coolest ones!



I love AILA  
PRON VERB NOUN

The aim is to **keep sentences containing a verb.**

Sentences containing **verbs** are the coolest ones!



Sentences containing verbs are the coolest ones!  
NOUN VERB NOUN VERB DT ADJ NOUN

*For each bigram, it extract the original sentence containing it and the adjacent sentences.*

# 1. AILAE - Preprocessing

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## > Text Summarisation



*The winners are those sentences containing the most frequent words.*

The aim is to **summarise the text to improve entity recognition.**

*For each sentence linked to a certain bigram:*

- 1. it tokenises all sentences and calculates the frequencies of each word;*
- 2. it calculates the score of each sentence by adding up the frequencies of the words in the sentence;*
- 3. it extracts the sentence with the greatest score.*

# 1. AILAE - Preprocessing

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## > Entropy Measurement

*Is the loss of information negligible?* → **Shannon's Entropy**

The aim is to **avoid loss of information** during summarisation.

*It evaluates whether the loss of information between the original set of sentences and the chosen sentence is negligible.*

# 1. AILAE - Named Entity Recognition

## > Sentence Tokenisation

*I am pretending to be a great long text. This is a sentence. Another sentence here. Are you enjoying the talk?*

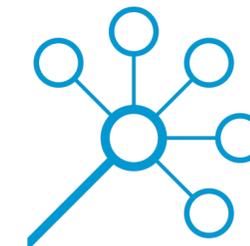


[I am pretending to be a great long text],  
[This is a sentence],  
[Another sentence here],  
[Are you enjoying the talk]

## > Entity Recognition

The **Mona Lisa** is a **sixteenth century oil painting** created by **Leonardo**. It's held at the **Louvre** in **Paris**.

0 persons	1 work	0 organisations	1 place	0 events	4 concepts
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DANDELION API



**Entities and synonyms!**

## > Sentence Gathering

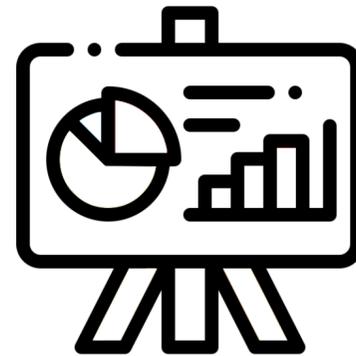
*For each entity, we gather all the sentences containing the entity or its synonyms in the original text.*

# AILA Methodology

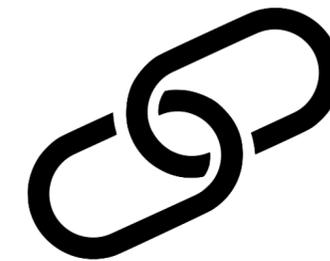
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1. AUTOMATED ASSET  
EXTRACTION



2. LIKELIHOOD  
DETERMINATION  
THROUGH AILA



3. COMBINED  
LIKELIHOOD  
DETERMINATION

## 2. Likelihood Determination Through AILA

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The **AILA Classifier (AILAC)** addresses this second challenge.



## 2. AILAC - Fairness

It indicates how **fair**, proper and clean a text is, regarding the *users' privacy concerns*.

<u>Fairness per asset</u>	<u>AILA Likelihood</u>	
0 - 0.20	5	<b>VH</b>
0.21 - 0.40	4	<b>H</b>
0.41 - 0.60	3	<b>M</b>
0.61 - 0.80	2	<b>L</b>
0.81 - 1	1	<b>VL</b>

AILA LIKELIHOOD DEFINITION

AILA Likelihood for dummies

$$L = 1 - F$$

## 2. AILAC - Dataset

We got 500 sentences enriched with *text augmentation* and *synonyms*.

A screenshot showing four cards representing different services. Each card has a logo, a grade, and a list of items with status indicators (red 'x', yellow 'down', green 'up', or a plus sign).

- Facebook (Grade E):** 6 items. 5 red 'x' (Facebook stores your data, identity used in ads, can read private messages, can view browser history, deleted content not really deleted), 2 yellow 'down' (keeps user logs, app requires broad permissions), 1 plus sign (contribute to rating).
- Amazon (Grade E):** 8 items. 7 yellow 'down' (terms may change, third-party cookies, tracks on other websites, can delete account, can license content, personal data for marketing, waive class action), 1 plus sign (contribute to rating).
- Reddit (Grade E):** 7 items. 3 red 'x' (can read private messages, sign away moral rights, can delete content), 4 yellow 'down' (can share info, tracking via cookies, may keep data, ignores DNT header), 1 plus sign (contribute to rating).
- Wikipedia (Grade B):** 7 items. 4 yellow 'down' (can delete account, may use tracking pixels, reduced time for legal action, no warranty), 2 green 'up' (publish under free licenses, resist legal requests), 1 plus sign (contribute to rating).



AILAC corpus consists of over 100.000 labelled sentences.

## 2. AILAC - Model

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The dataset is split into 2 parts:

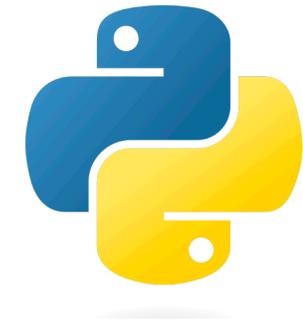
- 75% training
- 25% testing

The labelled sentences are transformed into a *2-D feature matrix*.

The *Relu function* is chosen as activation function of the first layer, the *Sigmoid function* for the second layer and the *Adam function* for the optimisation.

The model gets trained for *15 epochs* using the *binary cross-entropy function* as loss function, 0.0001 as learning rate, and 50 as batch size.

The model has an **accuracy of 96%**.



## 2. AILAC - Model

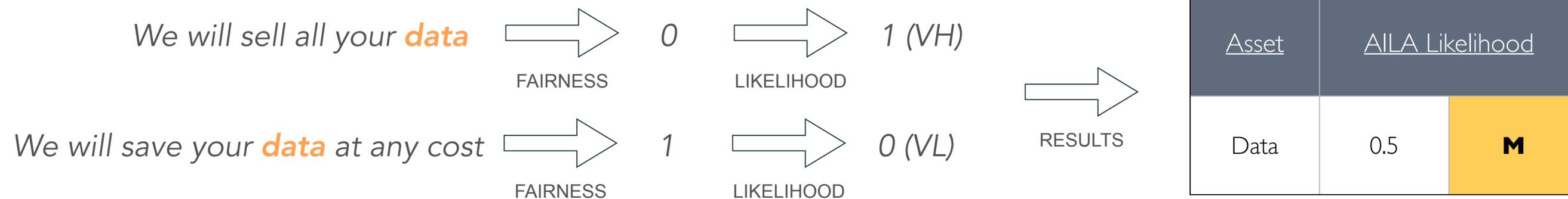
The model is used to evaluate the **fairness** of the sentences extracted in the previous step.

For each entity, it calculates the fairness of the related sentences and assign the **mean fairness** to the entity.

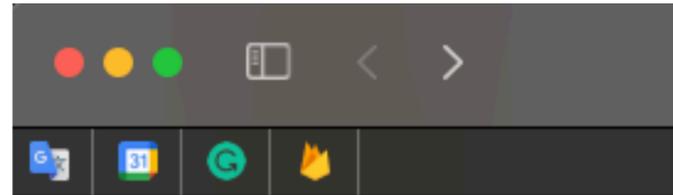
E.g.

**Asset:** *data*

**Sentences:** "We will sell all your *data*", "We will save your *data* at any cost"

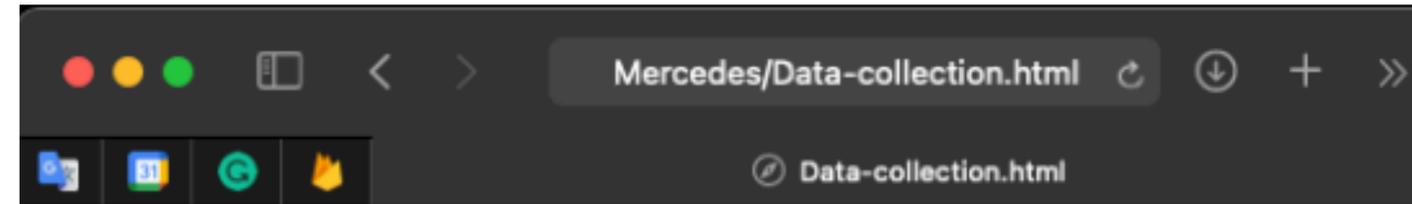


## 2. AILAC - Outputs Sample



- Satellite navigation
  - Fairness mean: 0.39
  - Likelihood: M
- Web portal
  - Fairness mean: 0.93
  - Likelihood: VL
- Vehicular communication systems
  - Fairness mean: 0.05
  - Likelihood: VH
- Vehicle tracking system
  - Fairness mean: 0.47
  - Likelihood: M
- Mobile app
  - Fairness mean: 0.44
  - Likelihood: M
- Data collection
  - Fairness mean: 0.49
  - Likelihood: M

LIST OF ENTITIES



	Data collection	Label
0	Your Choices Opt Out of data collection You can opt out of the collection of data via certain Mercedes me connect services by deactivating those specific services through the Mercedes me connect portal.	1.000000
1	Contact Mercedes me connect Support for additional information on how to opt out of data collection or deactivating services: 888- 628-7232 or me-connect.usa@cac.mercedes-benz.com.	0.980000
2	This Privacy Notice does not address the collection, use, or sharing of information regarding how you use or interact with our websites and mobile applications.	0.090000
3	Live Traffic, Navigation, Concierge, Car-to-X communications, Assist Services, Parked Vehicle Locator, Vehicle Tracker, Geofencing, Route Planning, Mercedes-Benz Apps, and Product Improvement services, for example, involve the collection of Geolocation Information to determine the location of your vehicle.	0.110000
4	In addition, some specific Mercedes me connect services may involve the collection and use of Driving Behavior Information.	0.260000

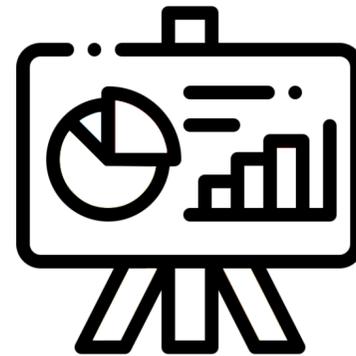
LIST OF SENTENCES FOR A SELECTED ENTITY

# AILA Methodology

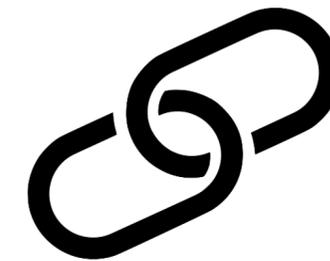
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1. AUTOMATED ASSET  
EXTRACTION



2. LIKELIHOOD  
DETERMINATION  
THROUGH AILA



3. COMBINED  
LIKELIHOOD  
DETERMINATION

### 3. Combined Likelihood Determination

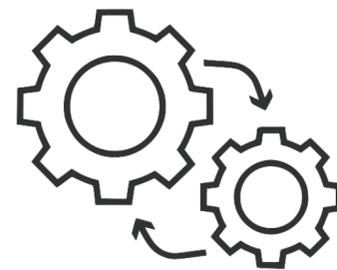
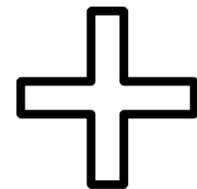
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AILA Likelihood can be used to *sculpt* the Likelihood outputted by a standard tool on a specific privacy policy.

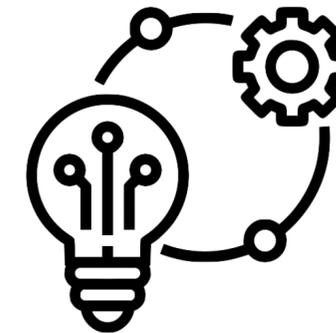
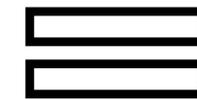
We combined AILA with *PILAR*.



AILA INTELLIGENT  
LIKELIHOOD



PILAR LIKELIHOOD



COMBINED  
LIKELIHOOD

# PILAR Reverse Engineering

**Impact**  $I = V \times d$

where I is the impact, V the asset value and d the degradation.

**PILAR Impact**  $I = V - \delta$  where  $\delta = \begin{cases} 6 & \text{if } d = 1 \% \\ 3 & \text{if } d = 10 \% \\ 2 & \text{if } d = 20 \% \\ 1 & \text{if } d = 50 \% \\ 0 & \text{if } d = 100 \% \end{cases}$

**Exponential fit**  $y = 1002.75e^{0.767241x}$  with  $r = 0.99$

E.g.  $V = 6 (= 100000), d = 20 \%$

$I = V - \delta = 6 - 2 = 4$

$I = V \times d = 100000 \times 20 \% = 20000 \simeq_{(Exp\ fit)} 3.9 \simeq 4$

Level	Value
0	1000
1	2150
2	4650
3	10000
4	21500
5	46500
6	100000
7	215000
8	465000
9	1000000
10	2150000

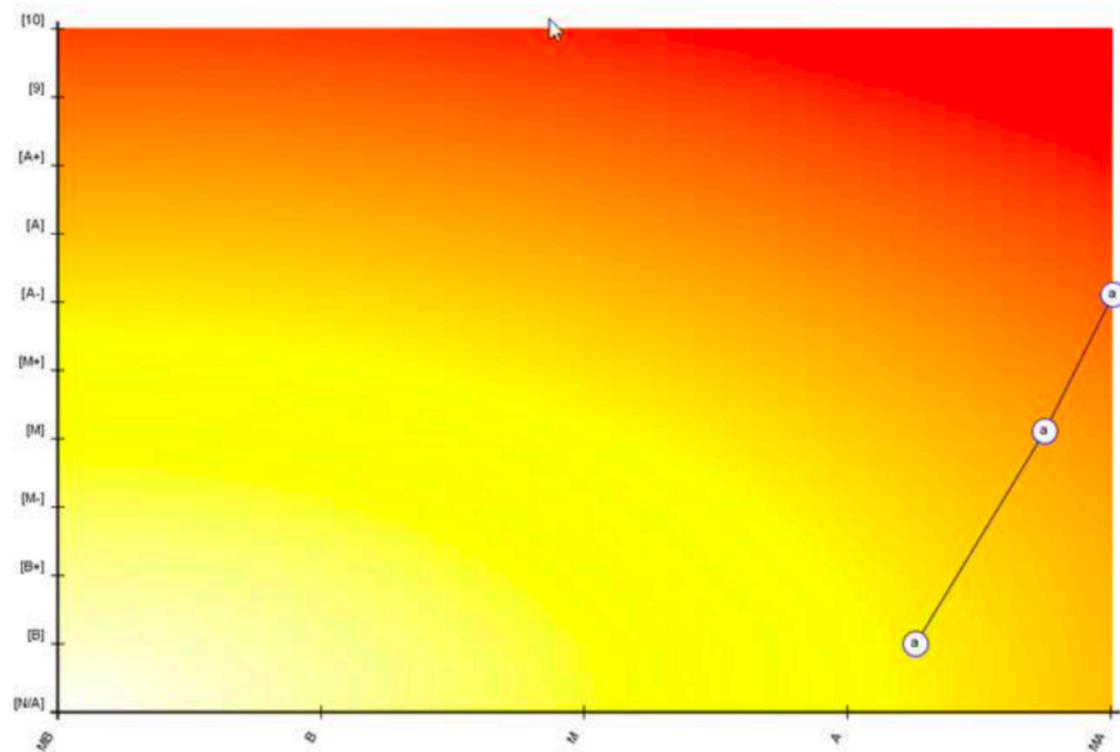
PILAR Levels Map

# PILAR Reverse Engineering

## PILAR Conjectured Risk

$$R = 0.6I + \lambda$$

where R is the risk, I the impact and  $\lambda = \begin{cases} -0.9 & \text{if } L = VL \\ 0 & \text{if } L = L \\ 0.9 & \text{if } L = M \\ 1.8 & \text{if } L = H \\ 2.7 & \text{if } L = VH \end{cases}$



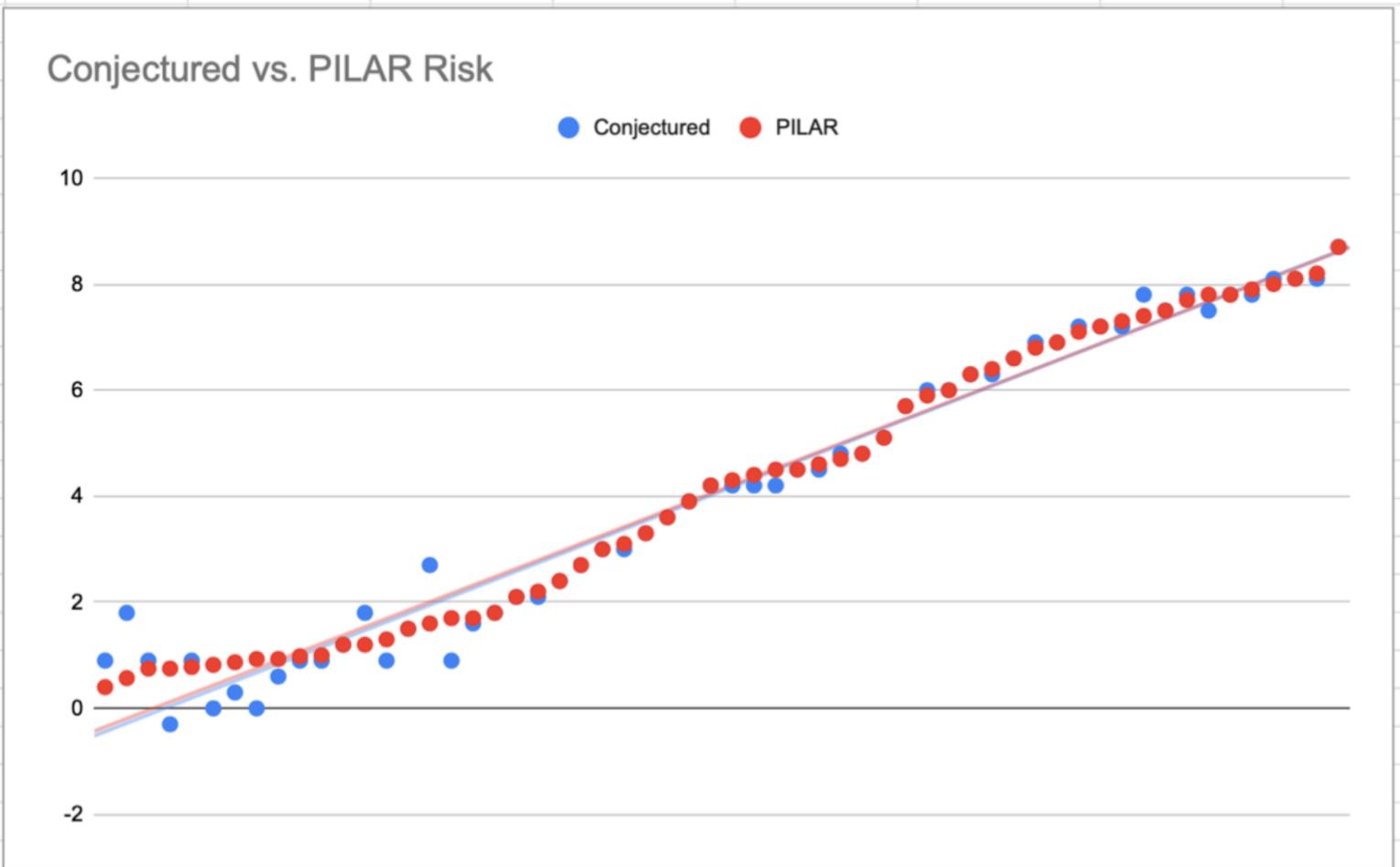
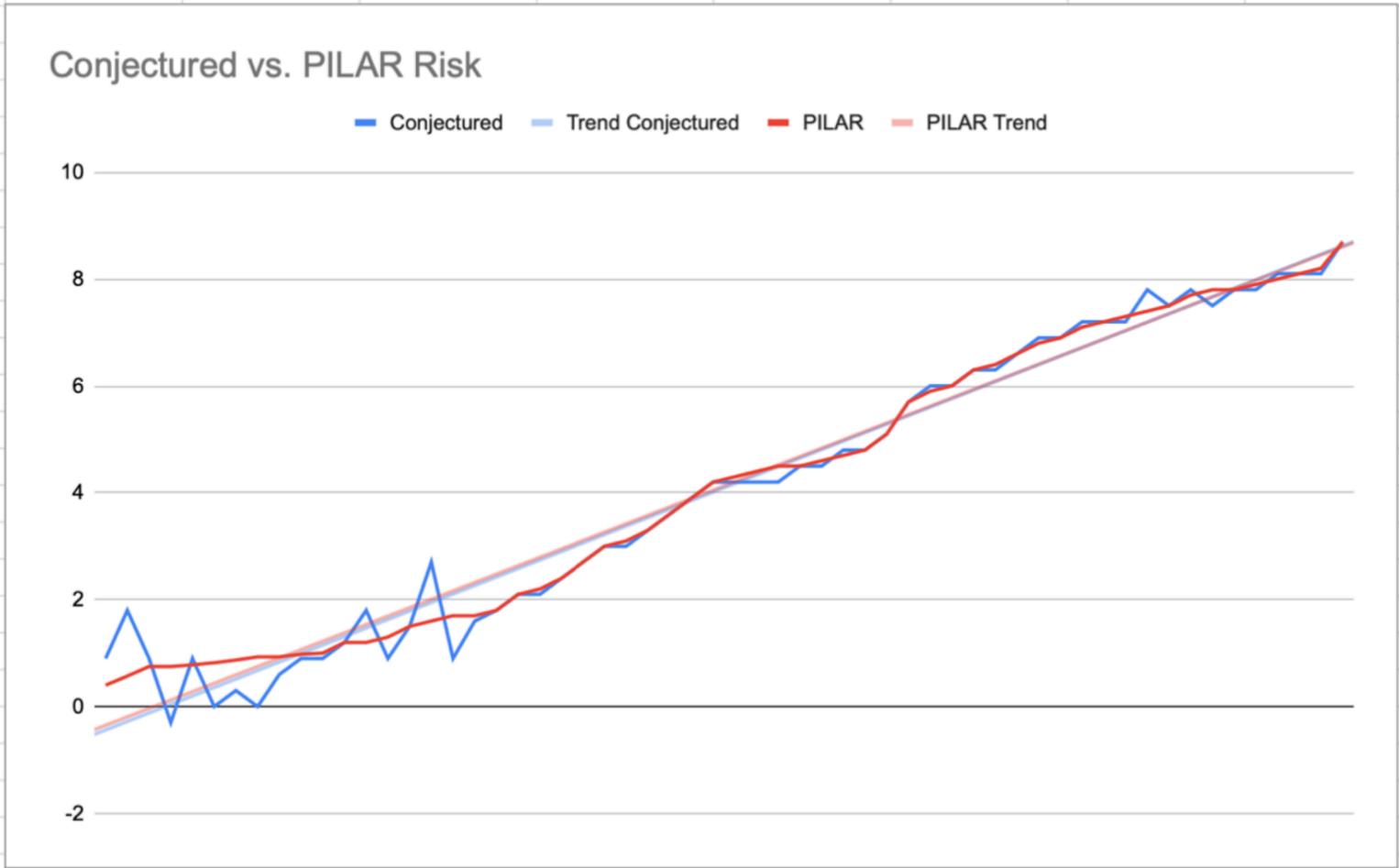
PILAR Heat Map

Risk	-0,9	0	0,9	1,8	2,7
10	5,1	6	6,9	7,8	8,7
9	4,5	5,4	6,3	7,2	8,1
8	3,9	4,8	5,7	6,6	7,5
7	3,3	4,2	5,1	6	6,9
6	2,7	3,6	4,5	5,4	6,3
5	2,1	3	3,9	4,8	5,7
4	1,5	2,4	3,3	4,2	5,1
3	0,9	1,8	2,7	3,6	4,5
2	0,3	1,2	2,1	3	3,9
1	0	0,6	1,5	2,4	3,3
0	0	0	0,9	1,8	2,7

PILAR Conjectured Map

# PILAR Reverse Engineering

Linear fit  $y = 0.97x + 0.15$  with  $r = 0.9909792073$



# Case Study - Automotive

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**Toyota** and **Mercedes** were the first two car brands in *Interbrand's 2020 Best Global Brands (BGB) Report*.

**Tesla** has a pioneer role on electric cars.

# Case Study - Assets Extracted from Policies

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<u>Policy</u>	<u>Original words</u>	<u>Words after summarisation</u>	<u>Entities</u>	<u>Assets</u>
Toyota	3526	768	<b>52</b>	<b>19</b>
Mercedes	1800	402	<b>57</b>	<b>17</b>
Tesla	6860	1164	<b>72</b>	<b>21</b>

# Case Study - AILA Results

PILAR Class	AILA asset	PILAR Threat	Toyota Privacy Policy			Mercedes Privacy Policy			Tesla Privacy Policy		
			PILAR Likelihood	AILA Likelihood	Combined Likelihood	PILAR Likelihood	AILA Likelihood	Combined Likelihood	PILAR Likelihood	AILA Likelihood	Combined Likelihood
Software	Application	Hardware or software failure	3	4	3.6	3	3	3.1	3	4	3.6
		Software vulnerabilities	3			3			3		
		Defects in software maintenance / updating	4			4			4		
		Malware diffusion	3			3			3		
		Software manipulation	3			3			3		
Communication	Location	Accidental alteration of the information	3	5	4	3	3	3	3	3	3
		Information leaks	3			3			3		
		Unauthorised access	3			3			3		
		Traffic analysis	3			3			3		
		Deliberate alteration of information	3			3			3		
		Destruction of information	3			3			3		

RESULTS SAMPLE

# Case Study - AILA Validation

We validated AILA with a tool promoted by ENISA. Mercedes's privacy policy was chosen as test data.

<u>Asset</u>	<u>AILA Fairness</u>	<u>AILA Likelihood</u>		<u>ENISA Likelihood</u>
Geolocation	0.23	0.77	<b>High</b>	<b>High</b>
Maintenance	0.38	0.62	<b>Medium</b>	<b>High</b>
Vehicle Tracking System	0.4	0.6	<b>Medium</b>	<b>Medium</b>
System	0.1	0.9	<b>Very High</b>	<b>High</b>
Mobile Application	0.44	0.56	<b>Medium</b>	<b>Medium</b>
Payment Information	0.05	0.95	<b>Very High</b>	<b>High</b>
Data Collection	0.49	0.51	<b>Medium</b>	<b>Medium</b>

AILA AND ENISA LIKELIHOOD SAMPLES

**AILA rocks!**

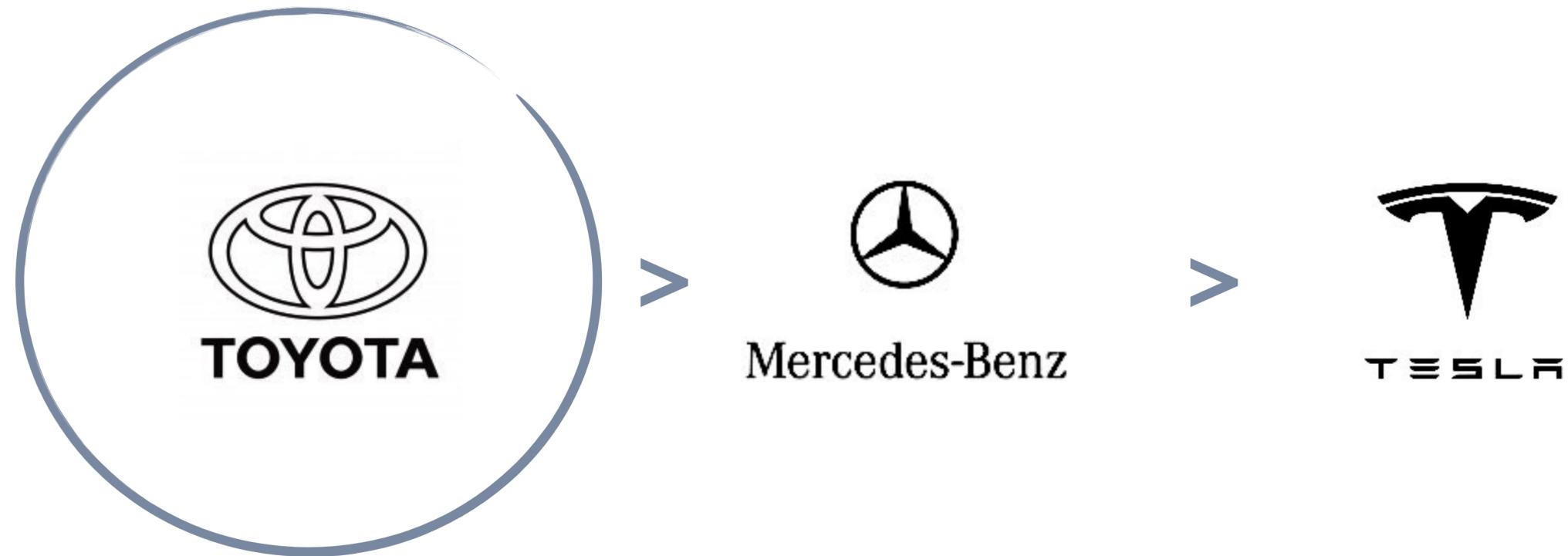
$$r = 0.93$$

$$r_s = 0.91$$

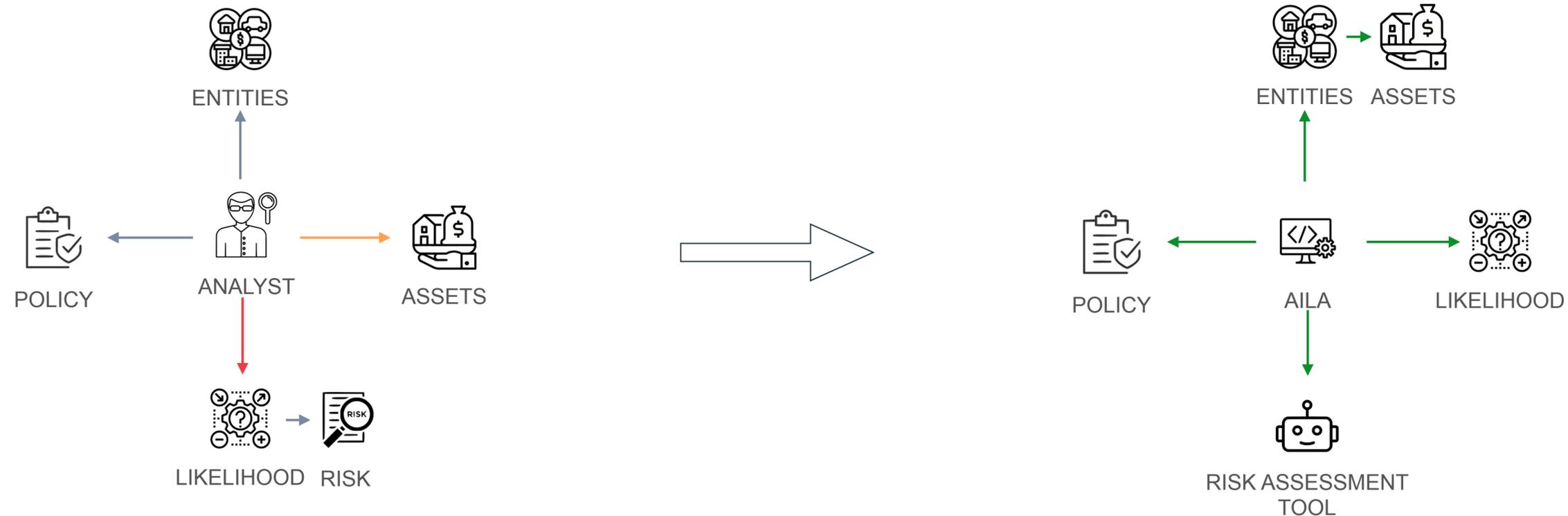
$$p - \text{value} = 0.00026$$

# Case Study - The Winner (or the Loser) is...

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# What's the Deal in Short?

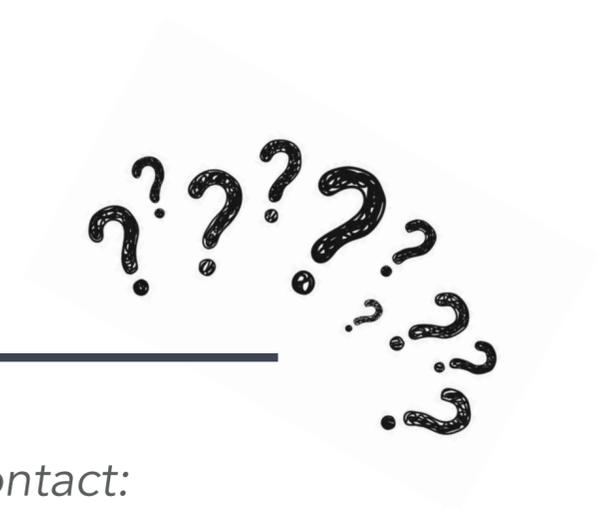


- > AILA reduces **human subjectivity** through risk assessment.
- > It facilitates **asset extraction** dramatically.
- > It automates the **analyst's perception** of a policy.

*Future work includes deeper semantic analysis and creation of a RA tool from scratch.*

# Q&A

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*For more information or questions, please contact:  
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