ML4PATENTS.COM WEBINAR SERIES

EPISODE 2

YOU HAVE MACHINE LEARNING QUESTIONS, WE HAVE ANSWERS!

Wednesday, August 25 | 11:00 am CST

Featured speakers:

Nigel Swycher
CEO of Cipher

Steve Harris
CTO of Cipher

Tony Trippe
Patinformatics

ML4Patents.com | CIPHER

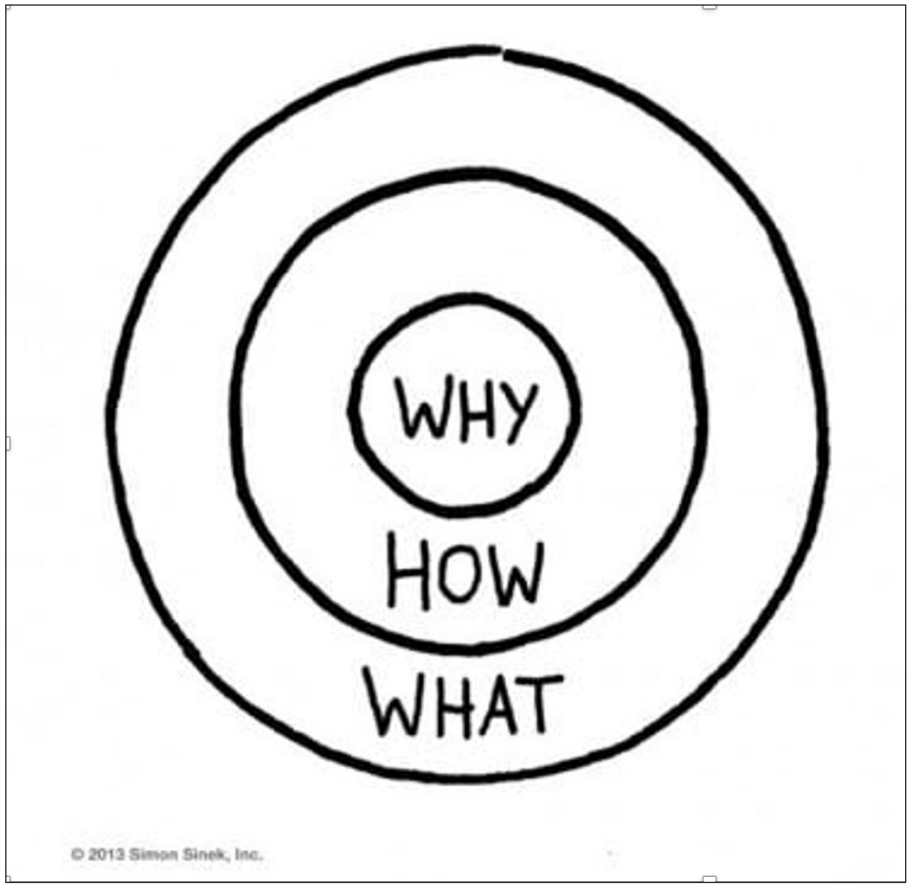
Welcome to Episode 2

Start with Why

Linear Law of Patent Analysis

- Create a toolkit of analysis tools
- **Understand the business need and the need behind the need**
- The need drives the question
- The question drives the data
- The data drives the tool

https://patinformatics.com/the-linear-law-of-patent-analysis-revisited/



Unleashing the strategic value of patents

Cipher enables patent owners to make rational decisions by providing strategic patent intelligence, powered by machine learning

"Cipher provides the data that we need, almost magically, using a lens that aligns with our company's view of the world."

Head of Patent Development  Red Hat

Strategic Patent Intelligence is different

Saves time & money

Conventional Boolean search requires time consuming manual cleaning. Cipher can read **61 million** in an hour

Automated patent to technology mapping

Patent classification system (CPC codes) cannot be used to map patents to company taxonomies

Objective, repeatable results

Automation provides analytics on demand, and achieves consistency

Strategic insights

Cipher delivers evidence for strategic decision-making in response to increasing pressure to communicate patent strategy

The importance of patent strategy

Corporate benchmarking is critical for patent strategy, competitive intelligence, budget management and pruning

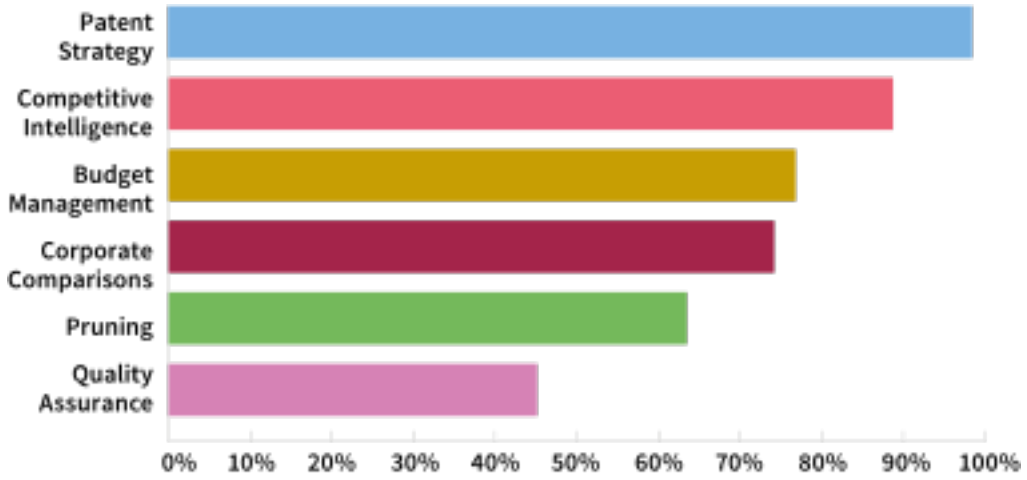
"It's critical to have benchmarking data because you don't want to operate in a vacuum."

Andreas Iwerback
Head of Technology & IP Intelligence, Husqvarna

"Benchmarking supports the communication of our approach, our strategy and why we are building the portfolio in the way that we are."

Gilbert Wong
Associate General Counsel for Patents, Facebook

Why do you benchmark your patent portfolio?



Source: Cipher IAM Benchmarking Survey 2020

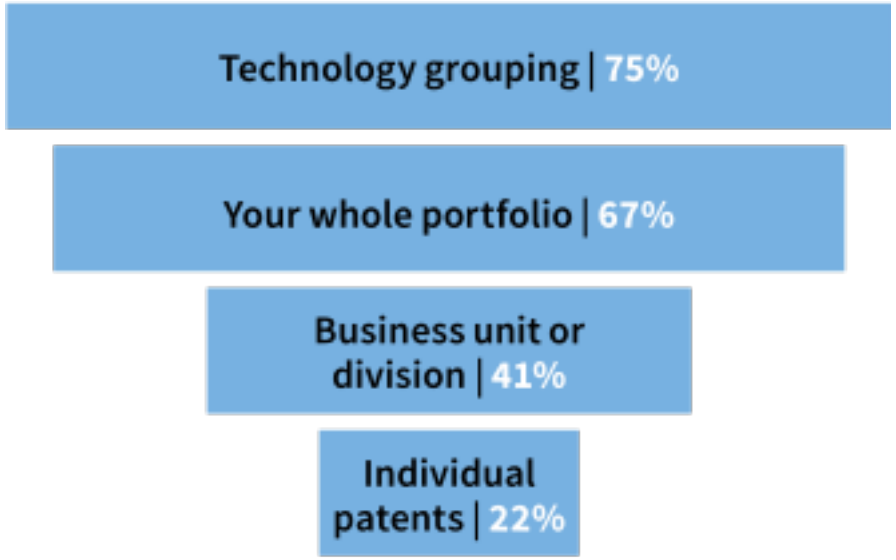
Refer to **Dispelling the Benchmarking Myth**
How Machine Learning increases efficiency and reduces cost, March 2021

Technology level analysis

There is a need for a granular and consistent approach

> "Benchmarking at the technology level is the only way to compare 'apples with apples' and to spot meaningful trends."
>
> *IP expert at a major European Semiconductor company*

What granularity do you benchmark?

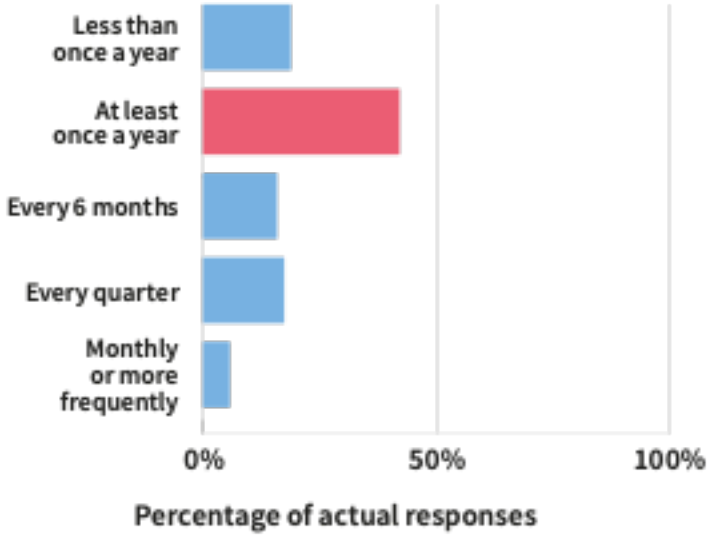


Source: Cipher IAM Benchmarking Survey 2020

Current data challenges

The size of the data challenge is not to be underestimated

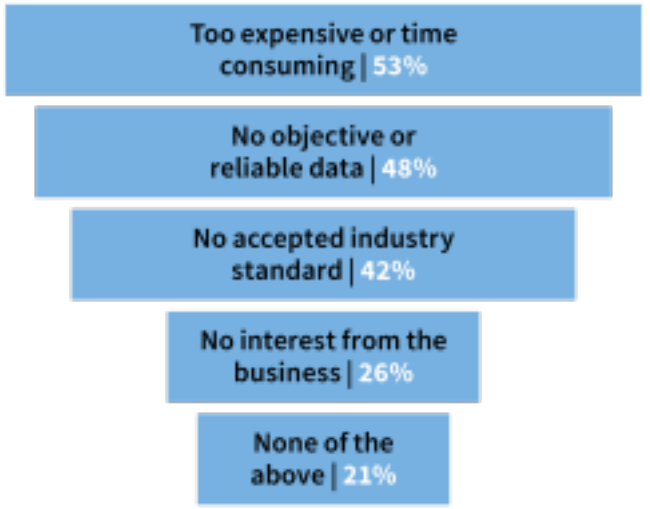
How often do you benchmark?



Source: Cipher IAM Benchmarking Survey 2020

88% of companies are benchmarking at least once per year - structured data and process is needed.

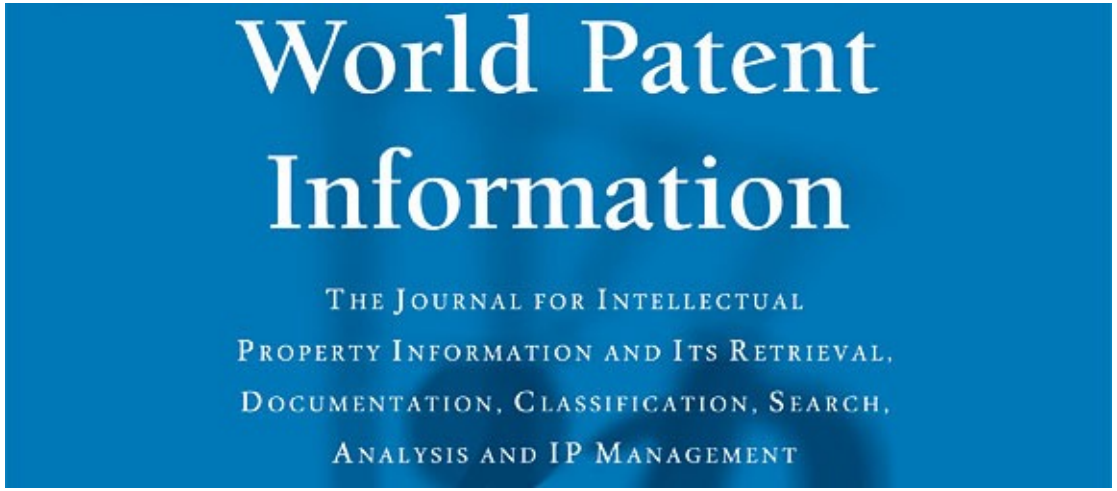
What are your challenges?



Source: Cipher IAM Benchmarking Survey 2020

Time and **money** are challenges - new approaches required.
Data **reliability** and **consistency** are a significant challenge for many.

The qubit generation test



Construction and evaluation of gold standards for patent classification

Steve Harris[1], Anthony Trippe[1], David Challis[1], Nigel Swycher[1]

[a] info@cipher.ai, *Aistemos Ltd, 39-41 Charing Cross Road, WC2H 0AR, London, UK*
[b] info@patinformatics.com, *Patinformatics LLC, 565 Metro Place S. Suite 3033, Dublin, OH 43017, USA*

Abstract

This article discusses options for evaluation of patent and/or patent family classification algorithms by means of "gold standards". It covers the creation criteria, and desirable attributes of evaluation mechanisms, then proposes an example gold standard, and discusses the results of applying the evaluation mechanism against the proposed gold standard and an existing commercial implementation.

Keywords: Patent Classification, Evaluation, Artificial Intelligence, Information Retrieval, Deep Learning, Gold Standard

1. Introduction

There are a number of problems in the strategic patent decision making and portfolio management domain where artificial intelligence techniques can be applied. One of the more common is that of mapping patent assets to technologies, for example to perform patent landscaping, or for reporting on the contents of your own, or competitor portfolios. This is also one of the hardest tasks to perform mechanically, and has been identified as a source of friction in strategic patent decision making[1].

Conventional "mandrolic", or semi-automated solutions typically revolve around performing a boolean search over the assets to discover a superset of the assets to be identified, then manually reviewing returned results to determine if each individual asset falls into the desired class.

There are a number of compromises involved in this approach – predominantly related to the time taken to perform a thorough review of the technology domain, or the cost of outsourcing this work to external experts.

In addition there is also the issue of inconsistency of results rithms in a neutral way is extremely difficult, even for experts in the field, which makes it very difficult to answer questions such as "which operations are viable to automate?", and "how does the accuracy of AI algorithms compare to manual work?".

This article proposes an approach for generating gold standards for machine classification of patents, and presents one such example. It then describes a methodology to test against that gold standard, and presents the results of evaluation of a commercially available system against it.

In the following text, we use the binary classification convention of denoting the data labelled as positive (examples of in-scope patents) with $T_{\oplus}$, and those labelled as negative (counter-examples) with $T_{\ominus}$, where T denotes the training set, G the gold standard as a whole, and so on.

We will also describe the processes in set notation for brevity, though restrict the use to just $\cup$ (union), $\cap$ (intersection), $\setminus$ (set difference), and $|X|$ (set cardinality).

2. Prior work

2.1. Existing gold standards

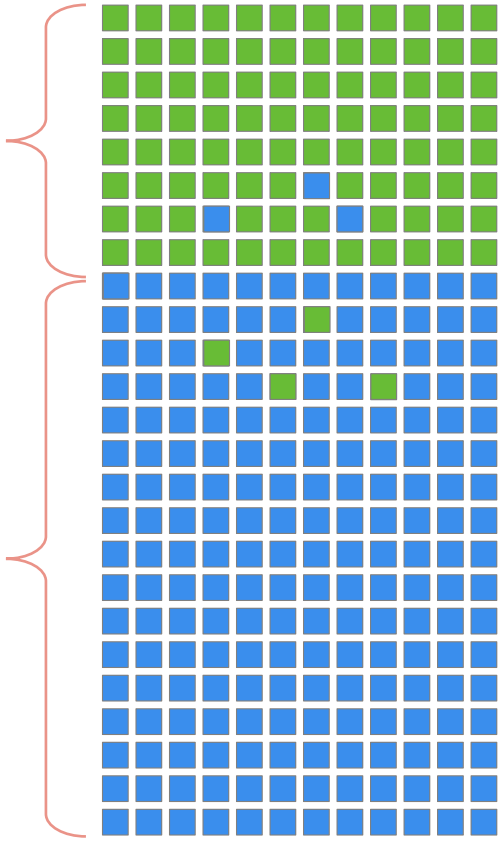
Measuring accuracy – returned results

Predicted Positives

Identified by classifier (96)

Predicted Negatives

Not Identified by classifier (204)



93 true positives
3 false positives

200 true negatives
4 false negatives

Precision

"Of the results found, what proportion are positive"

$$\frac{TP}{TP + FP} = 0.969$$

Recall

"Of all the positives out there, what proportion were found"

$$\frac{TP}{TP + FN} = 0.959$$

Can be combined to one number
$F_1 = 0.964$

Some common misunderstandings

“Building test sets is easy”

You can’t use any old data as a test set – it has to be very carefully checked, and representative.

Even tiny errors make the results meaningless.

“Testing is hard”

If you want to know how well a classifier does for your use case, just test it how you would use it for real.

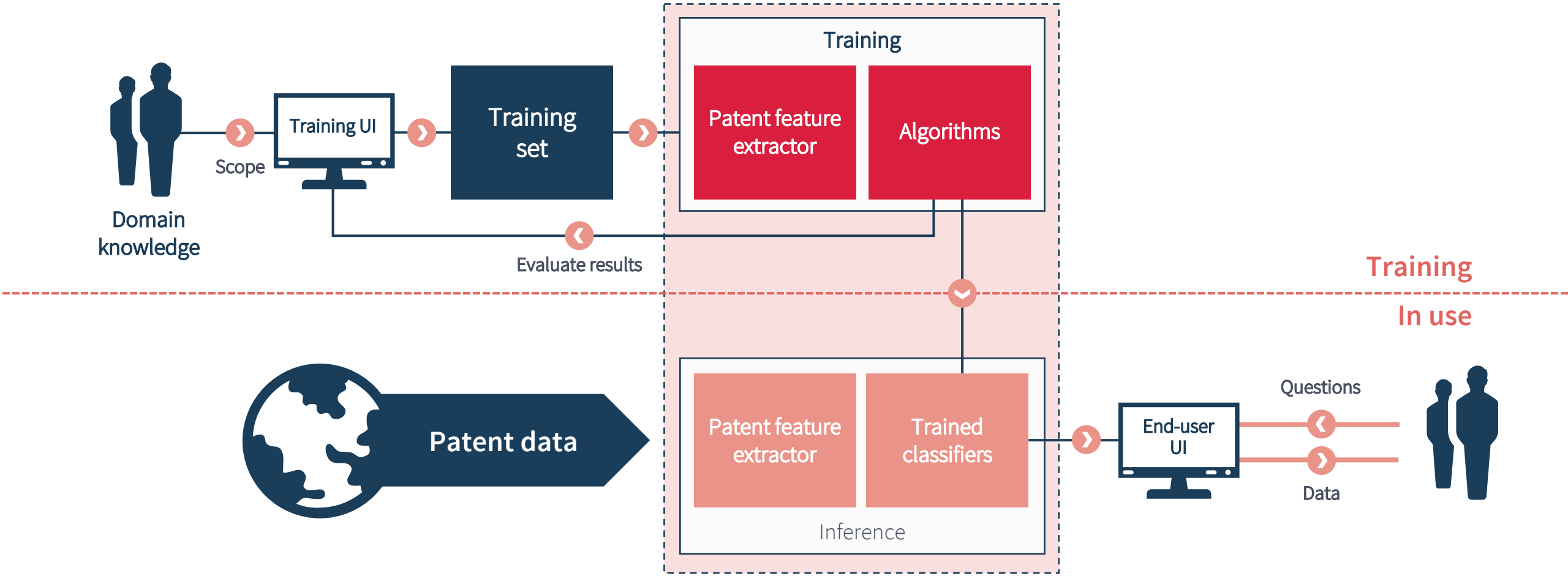
No synthetic test will ever be as useful.

“This classifier has 0.9 precision”

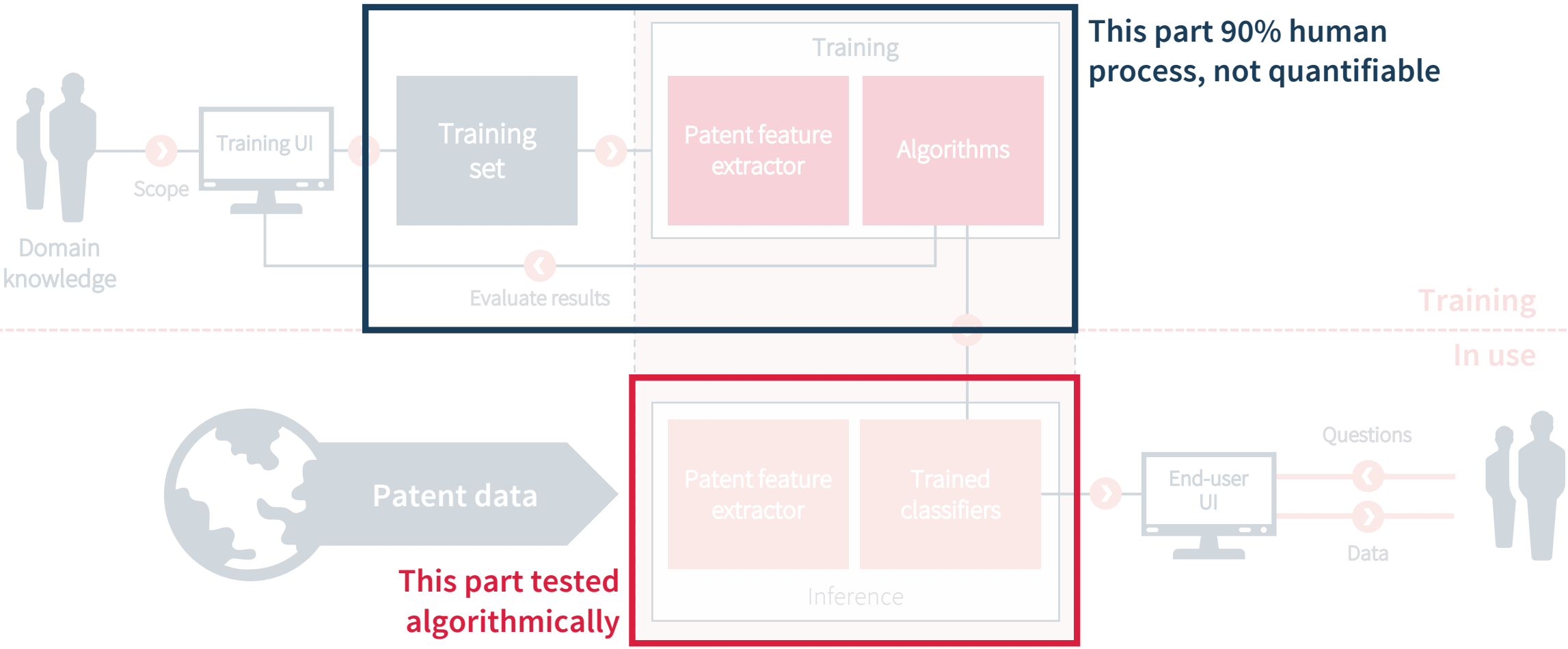
Classifiers do not “have” a precision and recall.

Precision and recall only mean anything with reference to a labelled test set.

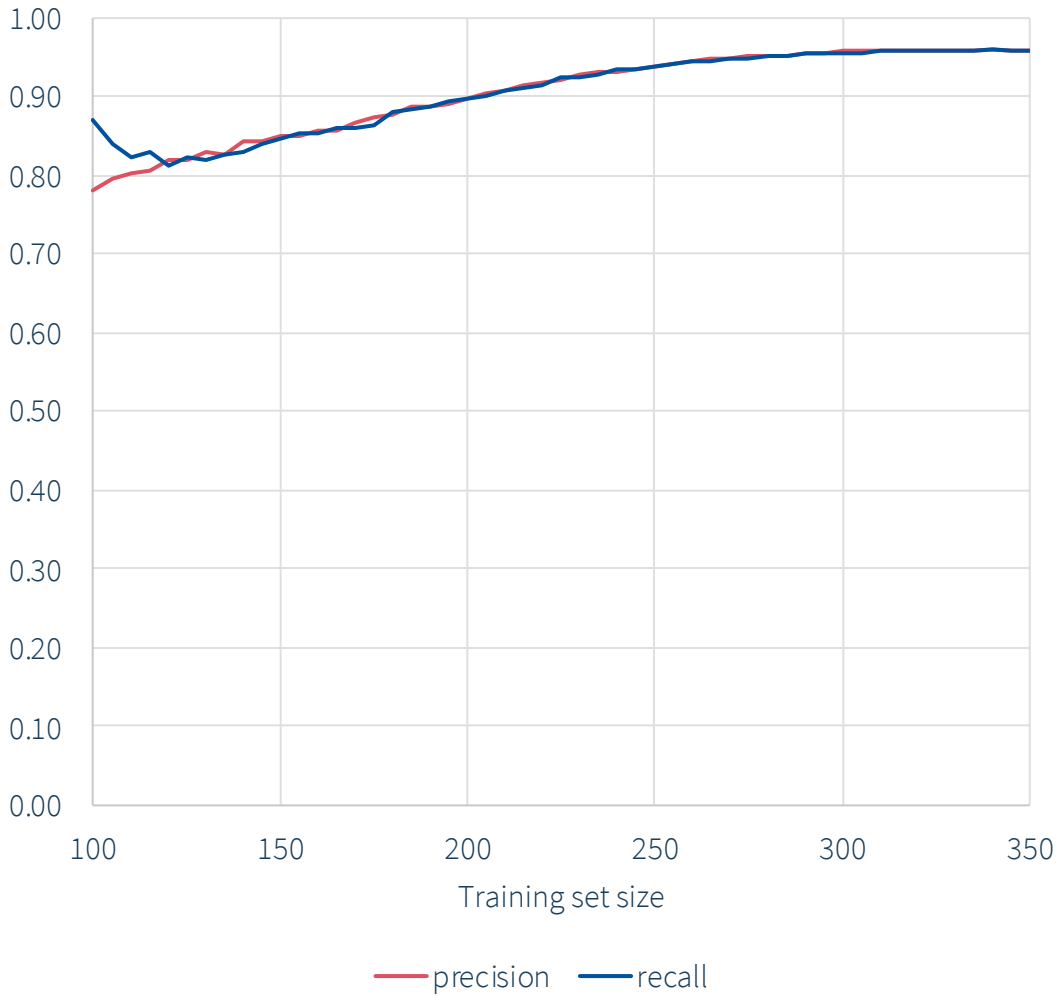
Training and using a classifier

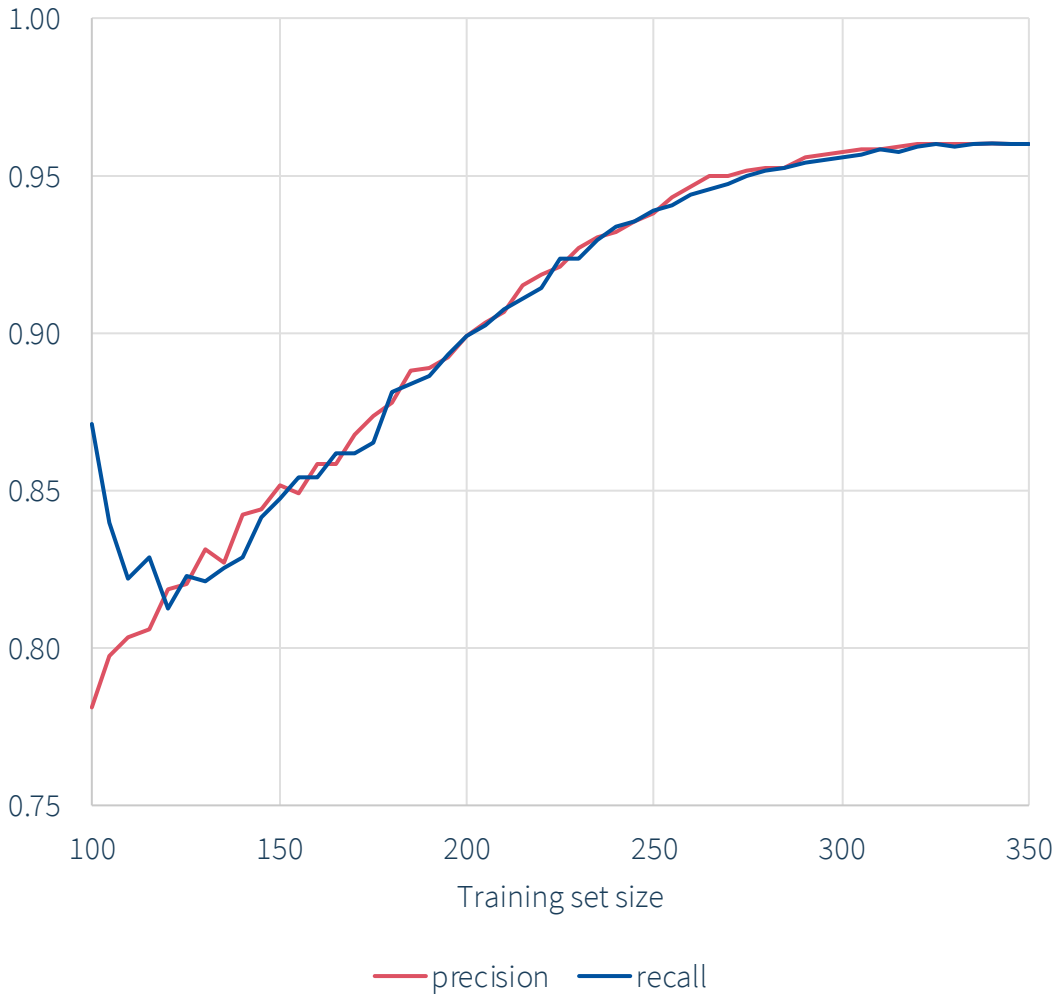


What can you measure?

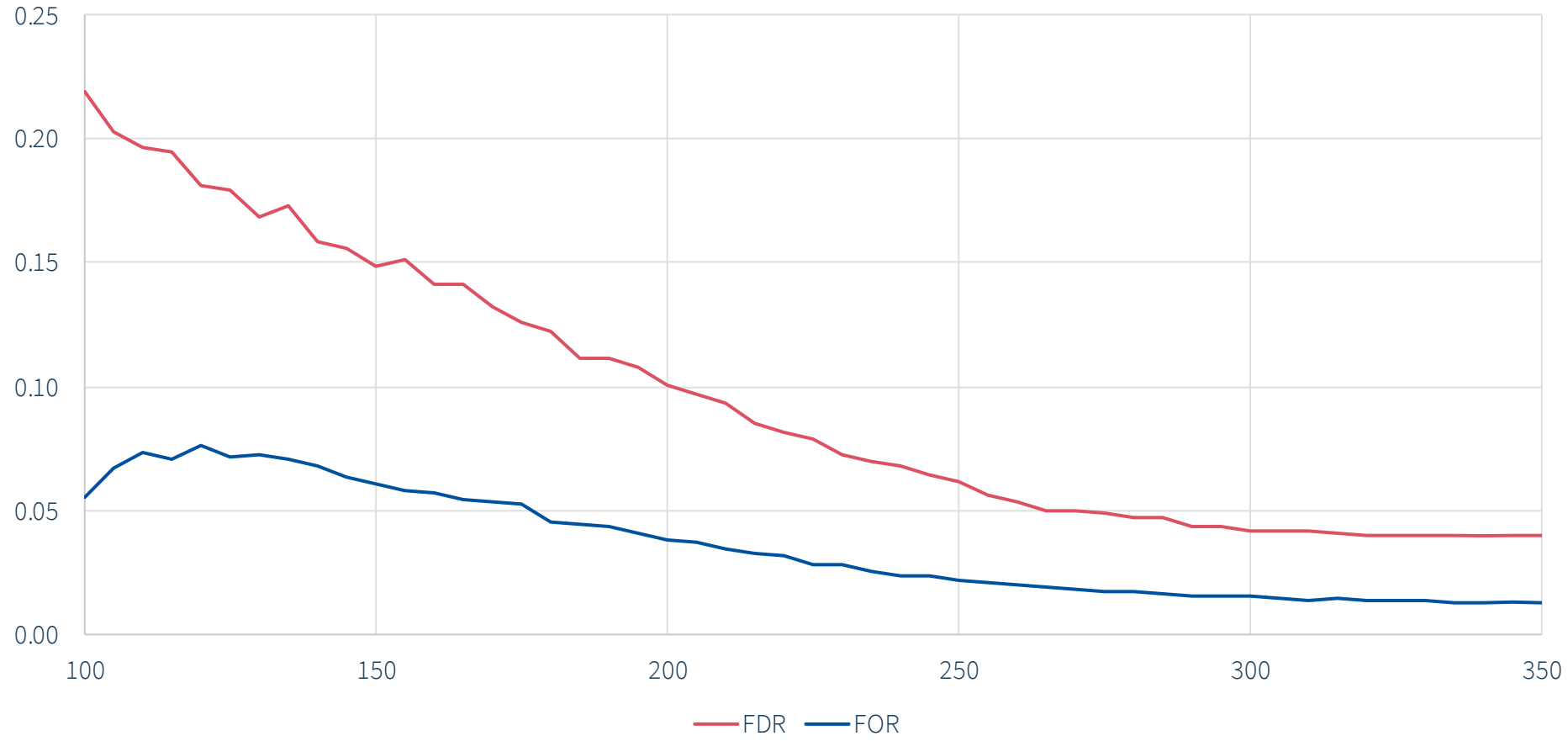


Results – precision and recall





False discovery and omission rates



What does training involve?

- Custom user interface for quickly training and evaluating classifiers.
- Allows you to upload known examples.
- Run evaluations and correct errors.
- See related patents that would be helpful for training.
- Train and cross-validate classifiers.

What data does the training process use?

Data that's used

Title and abstract – general background information

Claims – obvious why, uses a different embedding to title and abstract

Citations – information about topics that related to the patent

CPC class codes – component technologies, but it's less useful that you might think (see paper)

Data that's explicitly not used

Owner – we want to avoid any biases for/against specific companies

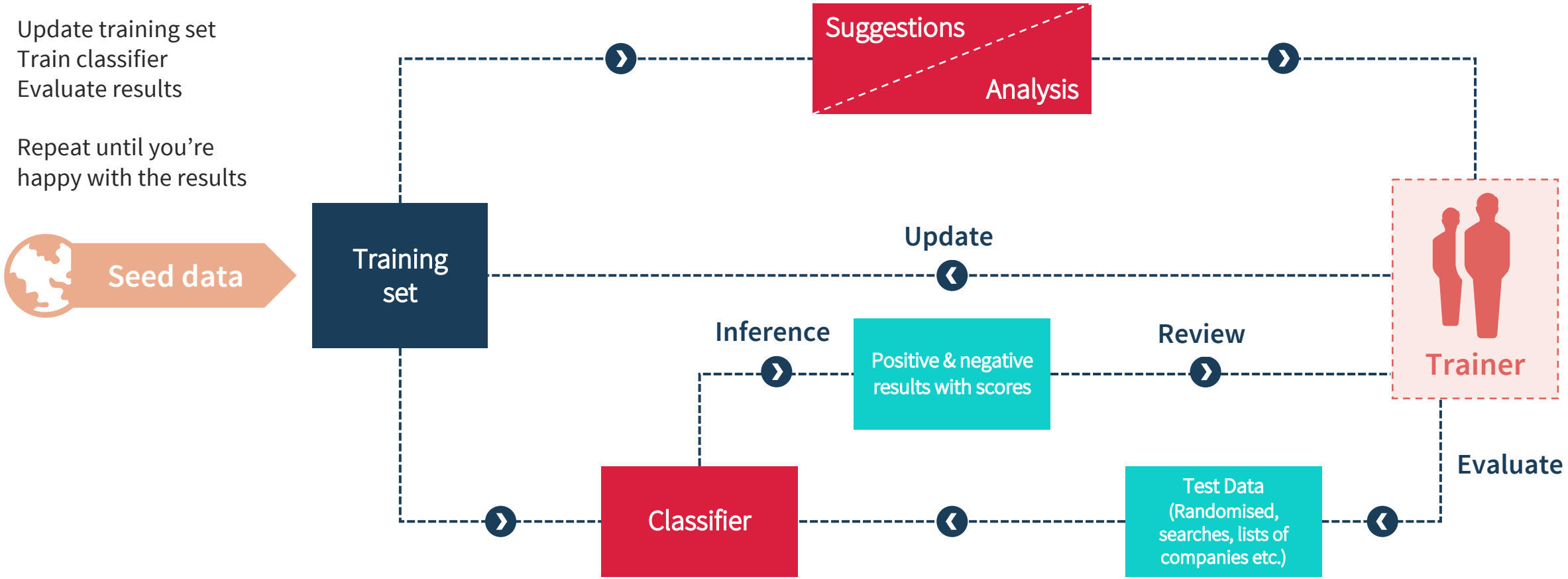
Inventor names – inventors correlate to companies

Non-English text – we machine translate to English where necessary

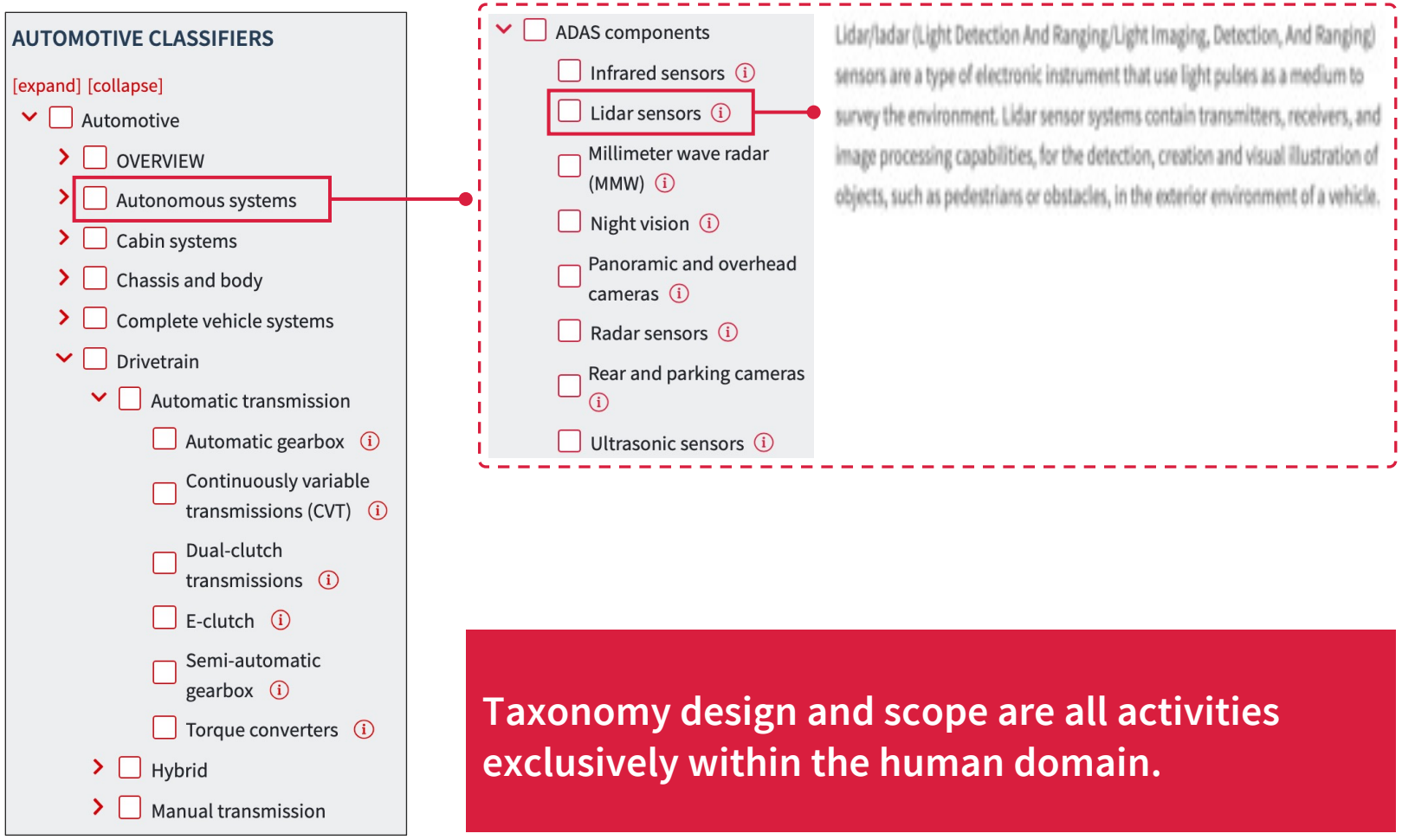
Cyclical training process

Update training set
Train classifier
Evaluate results

Repeat until you're happy with the results



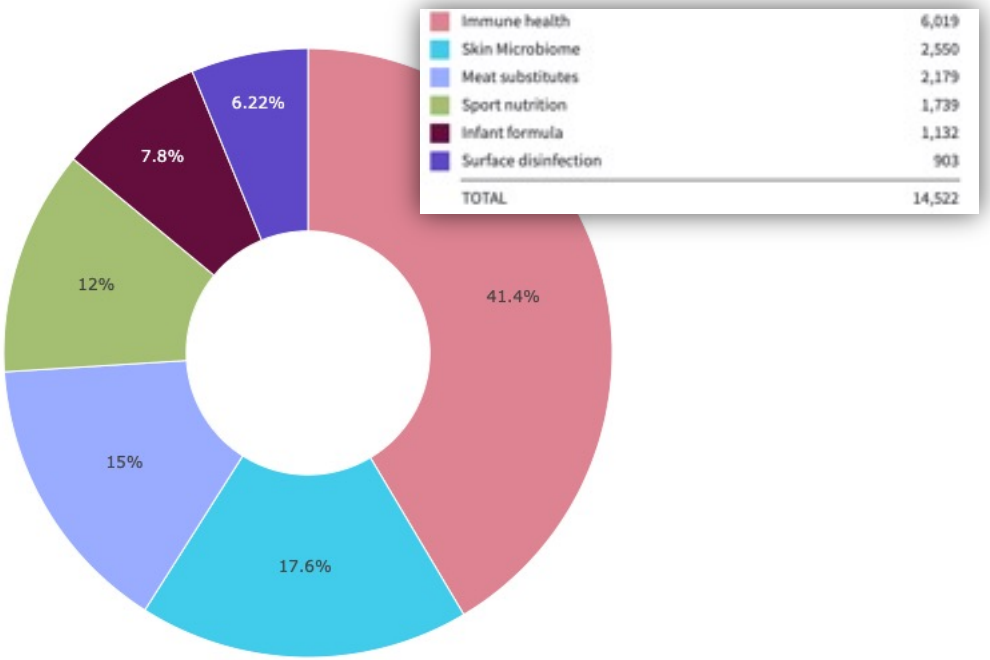
Custom taxonomies and automated classification



Taxonomy design and scope are all activities exclusively within the human domain.

Demo | classification without limits

1. Global Landscapes



Currently active patent families (granted or pending) by technology.

https://app.cipher.ai/report/1870e7083c/g/U3oWO/d/cIjAE

2. Selection of technologies against specific companies

	Toyota	Volkswagen	GM	Hyundai	Ford	Next 47	TOTAL
Lidar sensors	164	73	188	109	167	505	1,206
Radar sensors	126	160	98	41	21	289	735
Panoramic and overhead cameras	82	58	32	58	19	441	690
Rear and parking cameras	69	36	23	68	28	433	657
Ultrasonic sensors	52	36	1	37	13	122	261
Millimeter wave radar (MMW)	45	0	1	1	0	120	167
Night vision	12	13	2	15	9	81	132
Infrared sensors	4	3	2	6	6	37	58
TOTAL	554	379	347	335	263	2,028	3,906

Currently active patent families (granted or pending) by organisation and technology.

https://app.cipher.ai/report/81a8b3128b/g/selected/d/P11hY

CIPHER