ZY LAB
an IPRO company

# Europe Show

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## Bridging the Gap between Legal and Technology

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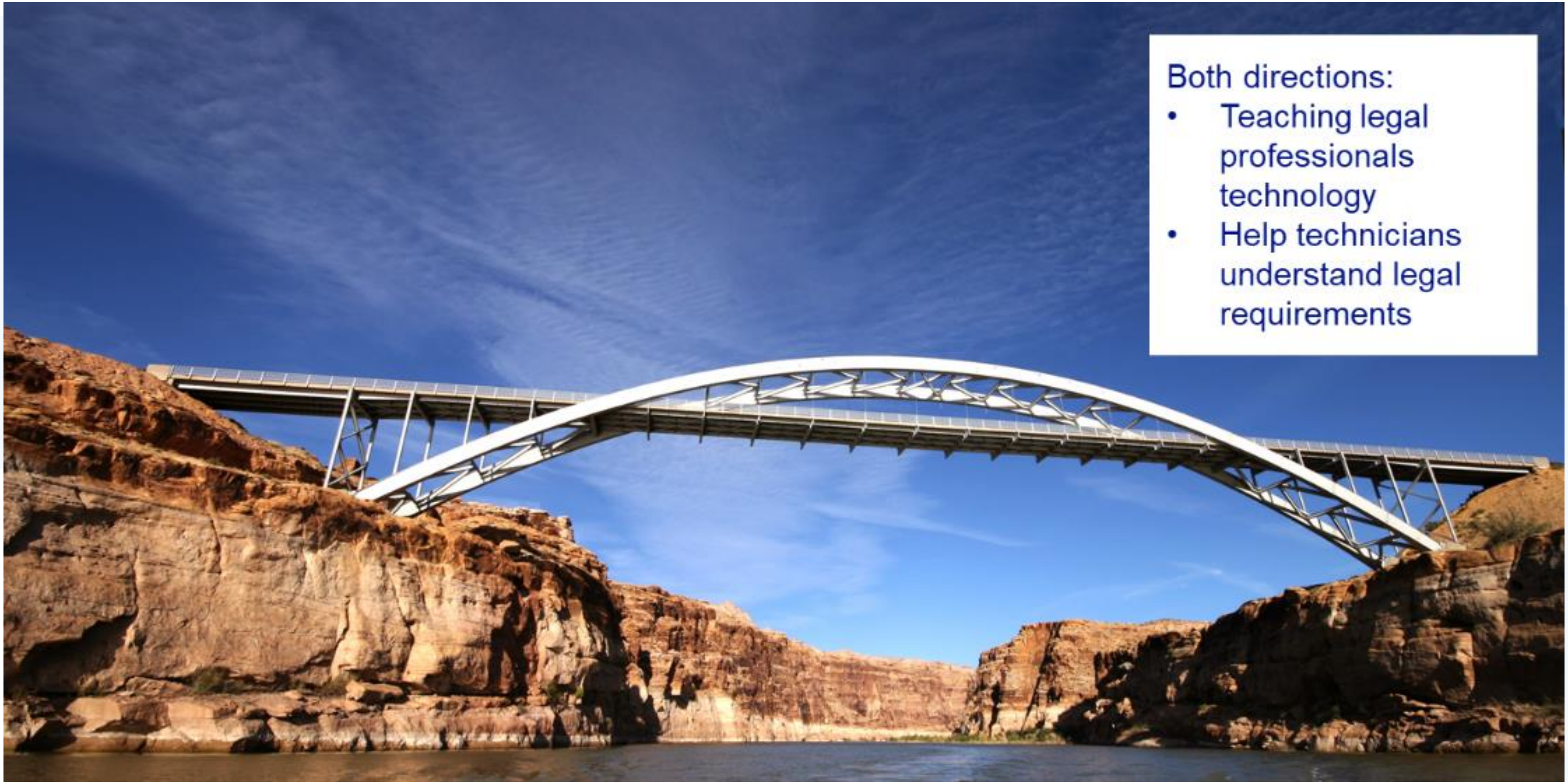
# Legal Technology & Legal Defensibility



# Legal Defensibility

When using technology in the legal domain, it is important to take the following requirements in account:

- Applicable legislation: which legal framework(s) apply? Are there any contradictions? Can technology address these?
- Ethical standards.
- Solid quality control on all automatic and manual actions.
- Understand where there is a risk for bias. Explain and document how this can be prevented.
- Transparency of technology: you need to be able to explain it, also to laymen.
- Robustness of technology: what happens with faulty or noisy input data?
- Reproducibility of technology. Using the same algorithm on the same data should get you the same results, also at a later moment in time
- Documentation: *Chain of Custody en Audit Trails* (who did what when, *inclusion*-, *exclusion*- and error reports)
- Safeguarding forensic integrity of the data and the process
- Is there (international) case law on the use of this technology? Has the technology been challenged in court before?

**THIS IS WHAT LEGAL PROFESSIONALS SHOULD ASK QUESTIONS ABOUT!**

**This is what should be included in a framework dealing with legal defensibility & eDiscovery technology**

# Examples of Bad Science versus Bad Ethics

## Bad Ethics

- No compliant to applicable legislation.
- Not being prepared for compliance with possible future legislation.
- No accountability for ethical values and standards.
- Prejudice or discriminative bias in data sets for machine learning.
- No transparency of algorithms.

## Bad Science

- Not being aware of any simplifications of real-world situations or limitations of applicability in the algorithms or mathematics you use.
- No objective quantitative validation of your algorithms or implementation.
- Using wrong quantitative validation measurements. E.g. using accuracy instead of precision & recall on unbalanced data sets.
- Creation of validation sets by just one individual: risk of human bias.
- Not measuring the disagreement between different individuals when using multiple individuals to create data sets (kappa distance).
- Selection or measurement bias in data sets for machine learning.
- Not testing algorithms against noisy input data.
- Jumping to conclusions: correlation does not imply causation.
- Not using forensic safe-guards (security, chain of custody, checks and balances, …)
- Marketing …

# Responsible & Defensible use of Legal Technology

| Law | Ethics | Algorithms & Mathematics | Software Implementation | Use by end-user (forensics) |
|---|---|---|---|---|
| Which Laws & Jurisdiction Apply? | Compliant with Ethics and Future Legislation? | Right model? Right mathematics? Any unacceptable simplification? | How are the algorithms implemented, trained, tested and how is quality measured? | How does the end-user apply the technology in a legal application? Are all safeguards applied? |
| All | All | Data Scientists | Software Development | End User |

# Legal Requirements

# Applicable legislation depends on use case

- US: Public Records Requests (State, City, County, University, …) & FOIA (Federal)
- NL: Wet Openbaarheid Bestuur (Wob)
- DK: Forvaltningsret
- UK & Ireland: FOIA

- Internal Security
- Internal Audit
- Compliance
- Comptrollers
- Raadsonderzoeken (NL)
- Parliamentary enquiries / Senate / Congress Hearing
- Office of the Inspector General (OIG).
- …


- Anti-Trust and Competition
- Financial Products
- Environmental
- Consumer goods
- Privacy
- Telecommunications
- Healthcare (if financed by government)
- Pharmaceutical
- Aerospace
- …

- Anti-trust and non-competitive behavior: price fixing, tender fraud.
- Other financial fraud
- Money laundering
- Drugs trafficking
- Organized Crime
- …

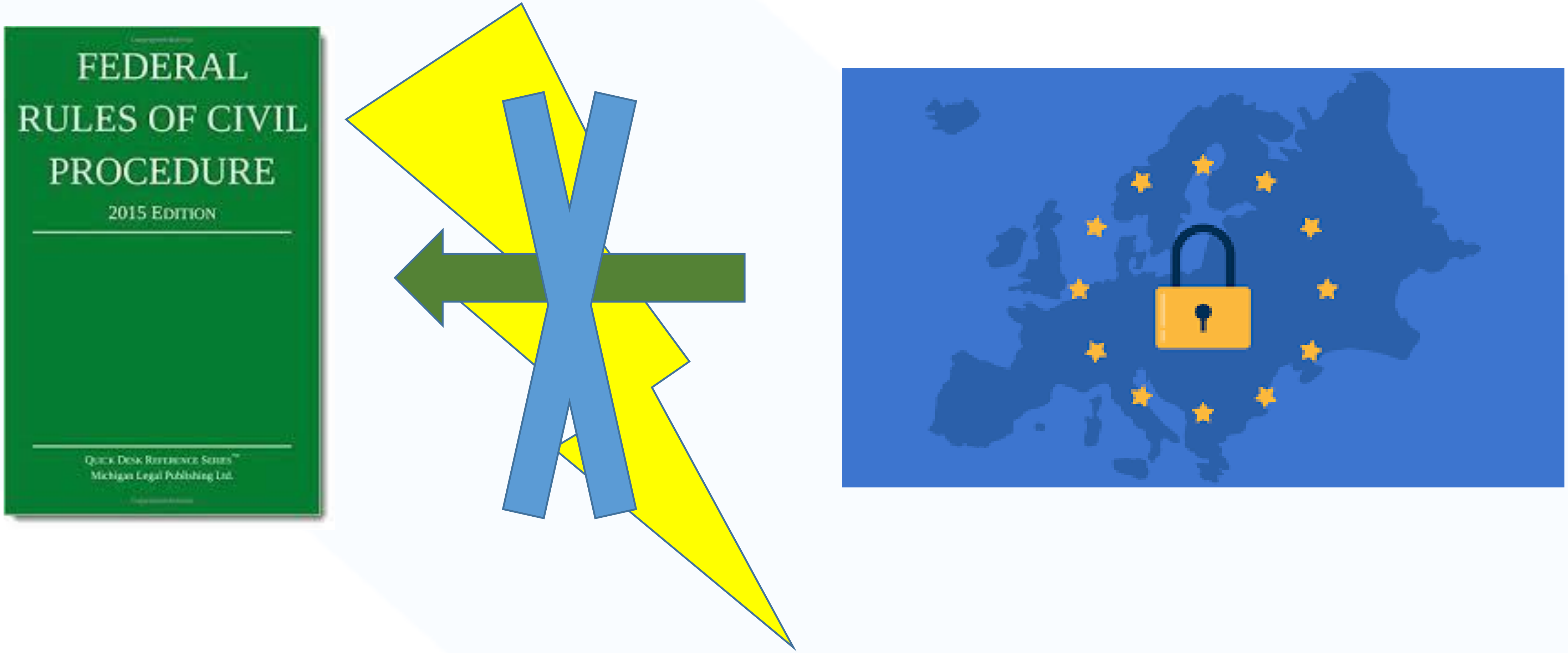
- Human Resource & Employment Disputes
- Intellectual Property & Patents
- Contract and Commercial Disputes
- Public Government Disputes (Bestuurdrecht)
- Bewijsbeslag
- …

- Data Subject Access Requests (DSAR), Inzageverzoeken).
- CCPA (US) / GDPR (EU) / AVG (NL) Data Storage (File) Analysis.
- Reporting to Subjects of Data Breaches

# What do you typically have to deal with?

- Privacy & data protection regulations
- Proportionality
- Subsidiarity
- Additional regulations and case law per use case? Recommended best practices? Mandatory audits for non-compliance?
- Copyrights, patents, specific contractual obligations, …

# Often (international) legislation is in contradiction to each other



# Large Controversy on Google Books Project

Google: “we’re not scanning all those books to be read by people. We’re scanning them to be read by Artificial Intelligence”


Outcome: the US District Court’s eventual ruling in November 2013 in Author’s Guild, Inc. v Google, Inc. took a more pragmatic view, holding that Google’s use of the works, including “a type of research referred to as ‘data mining’ or ‘text mining’” was “fair use” under US copyright law: Google Books provides significant public benefits. It advances the progress of the arts and sciences, while maintaining respectful consideration for the rights of authors and other creative individuals, and without adversely impacting the rights of copyright holders. In Europe courts decided differently!

# Ross versus West-Law (Thomson Reuters)

- Ross used law books from West-law to extract legal facts (using text-mining).
- Machine learning algorithms were trained with this data
- West-Law accused Ross of copyright violations.
- Interesting fact: most of West Laws data is based on public data (court verdicts) but is enriched (often also with text-mining).
- Ross ceased business and accused West-law of anti-trust behavior and abuse of monopoly positions

*Source: https://www.abajournal.com/news/article/ross-intelligence-to-shut-down-amid-thomson-reuters-lawsuit*

TECHNOLOGY

## ROSS Intelligence will shut down amid lawsuit from Thomson Reuters

BY LYLE MORAN

DECEMBER 11, 2020, 11:50 AM CST

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*Image from Shutterstock.com.*

ROSS Intelligence, which launched an AI-based legal research platform six years ago, announced Friday that it plans to cease operations early next year because of an ongoing copyright infringement lawsuit that Thomson Reuters brought against the company.

Thomson Reuters filed a lawsuit with the U.S. District Court for the District of Delaware in May, alleging that ROSS Intelligence had stolen "critical features" of Thomson Reuters' Westlaw legal research platform to develop its own legal research offering.

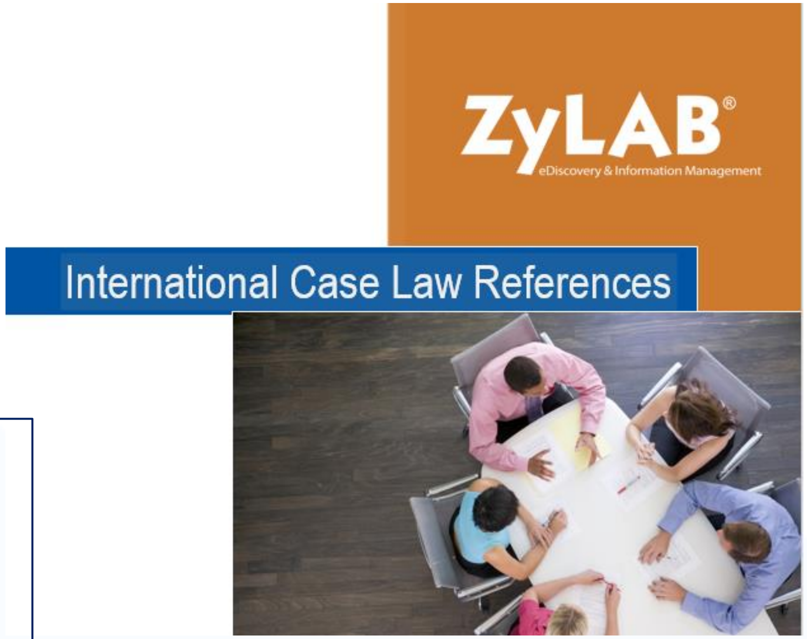
"Litigation is expensive—no matter how speculative the claims against you nor how worthy your position," ROSS Intelligence said in a statement on the company's website. "With our company ensnared by this legal battle, we have been unable to raise another round of funding to fuel our development and marketing efforts. Our bank account is running out, and we must cease operations in the new year."

ROSS Intelligence said as of Monday, it has stopped accepting new customers, and by Jan. 31, the platform will no longer be available.

"Between now and then, our priority is to help our current customers transition to other services," the company said.

# Existing case law on use of certain technology helps!

- Jurisprudence on the use of certain technology in earlier cases:
  - Has it been used?
  - Has it been challenged?
  - Did it survive such challenges?




ZyLAB technology has been used in the following international cases by the prosecution, the lawyers, chambers and other participants of the following international courts and tribunals:

- UN International Court of Justice for various cases and archives, including the Nurnberg files. More information: http://www.icj-cij.org/.
- UN International Criminal Tribunal for the former Yugoslavia (UN ICTY). More information: http://www.icty.org/.
- UN International Criminal Tribunal for Rwanda (UN ICTR). More information: http://www.ictr.org/.
- Extraordinary Chambers in the Courts of Cambodia/United Nations Assistance to the Khmer Rouge Trials (ECCC/UNAKRT) http://www.eccc.gov.kh/ and www.unakrt-online.org
- UN Special Court on Sierra Leone (UN-SCSL). More information: http://www.sc-sl.org/.
- Serious Crimes Investigations Team/United Nations Integrated Mission in East Timor (UNMIT) www.unmit.org
- United Nations International Independent Investigations Committee in Lebanon (UN IIIC)
- UN Tribunal for the Sea (UN ITLOS). More information: http://www.itlos.org/.
- European Union Rule of Law Mission in Kosovo (EULEX-Kosovo). More information: http://www.eulex-kosovo.eu/.
- European Union Anti-Fraud Department: OLAF: European Anti-Fraud Office | European Commission (europa.eu)

# 2012: Case Law on Assisted Review (TAR)

- The Honorable Andrew J. Peck served for 23 years (from February 1995 until his retirement in February 2018) as a United States Magistrate Judge for the Southern District of New York, including a term as Chief Magistrate Judge from 2004 to 2005.

- Judge Peck is recognized internationally for bringing electronic discovery competency to the attention of both the judiciary and bar. He is widely described as one of the first judges to tackle the subject of e-discovery head on. His landmark decision in the 2012 employment class action Monique Da Silva Moore, et. al. v. Publicis Groupe & MSL Group, was the first judicial decision approving the use of technology-assisted review (TAR). By 2015, Judge Peck declared in Rio Tinto v. Valle that it was black-letter law that if the responding party wished to use TAR, courts would allow it. In the third of his trilogy of TAR cases, Hyles v. City of New York, he stated that while he preferred the use of TAR, neither the requesting party nor the court could require a reluctant responding party to use TAR.

# Ethical Requirements

# Values and Ethics

Ethics or moral philosophy deals with systematizing, defending, and recommending concepts of right and wrong conduct.


Ethics seeks to resolve questions of human morality by defining concepts such as good and evil, right and wrong, virtue and vice, justice and crime.

Centuries of study into moral philosophy. Many different schools and views. There is no single school of thought that settles all moral questions.

# Ethics and Computer Science?

Association of Computing Machinery (ACM) defined 7 principles in relation to accountability and transparency of algorithms:

1. Awareness of bias
2. Access and redress to prevent discrimination
3. Accountability
4. Explanation
5. Data Provenance
6. Auditability
7. Validation and Testing

Sources: https://www.acm.org/ and https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf

# Computers are ruthless… fruit picking game

- Google’s AI got “highly aggressive” when competition got stressful in a fruit-picking game.
- Shoot other players at beginning of game.

# Scientific & Mathematical Requirements: preventing bad science

# Transparency of your technology

Know your algorithms, their mathematics, their assumptions and this their limitations!

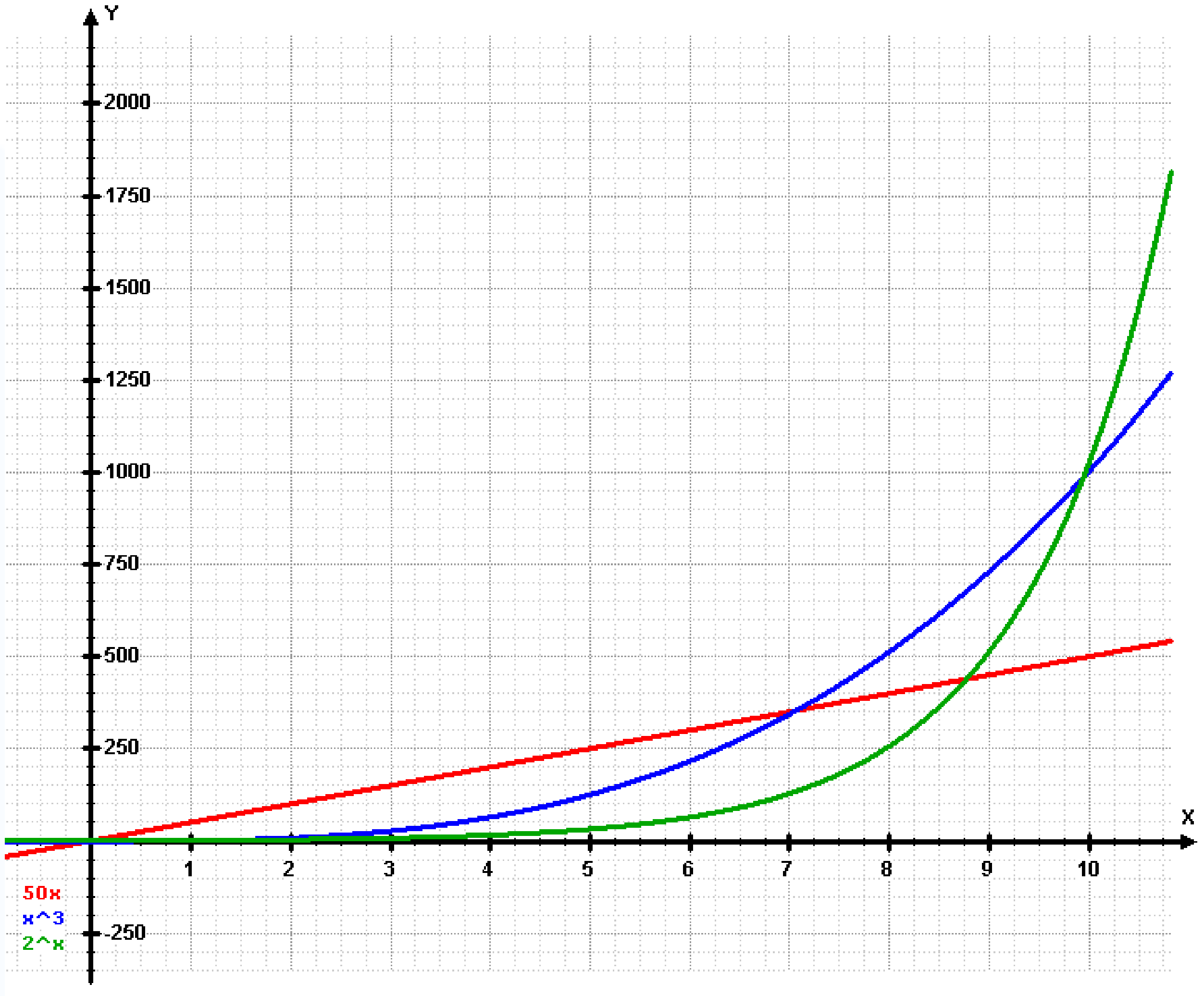
Also:

- Cultural invariance
- Temporal Invariance (other standards or values over time)
- Lacking domain expertise
- Internet based research: only popular data, not good broad un-biased spreading,. No provenance as well.
- Disagreeing judges when building data sets. Not measuring Kappa distances.
- Cherry picking in results
- Just stupid errors
- Simply overlooking exceptions (errors and omissions)
- Long tail of exceptions and rare occurrences

Can you explain the workings to laymen?

# Predicting COVID Outbreaks

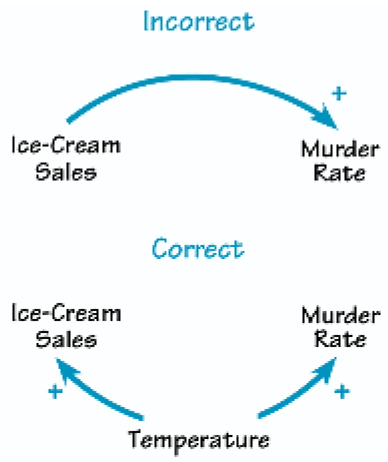
- Use the correct mathematical model
- Linear or exponential?



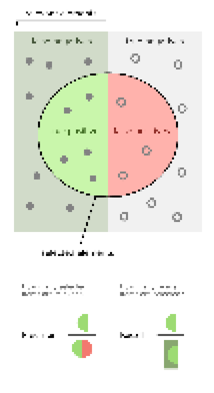
# *Primum non Nocere**: dealing with false positives

- Text mining and data mining would seem to provide a great deal of potential for inadvertent or deliberate misinterpretation of data.

Example: mining data extracted from a range of travel-related transaction databases (e.g., airline passenger manifests, railway ticket websites, etc.), to attempt to identify suspicious patterns of travel behavior that can be linked to named individuals. Support & Confidence: “*correlation does not imply causation*”




- Named entity recognition: error-prone, highly contextual sensitive, often well-informed guesswork: 90% precision on 100.000 patters, still leaves us 10.000 WRONG conclusions!



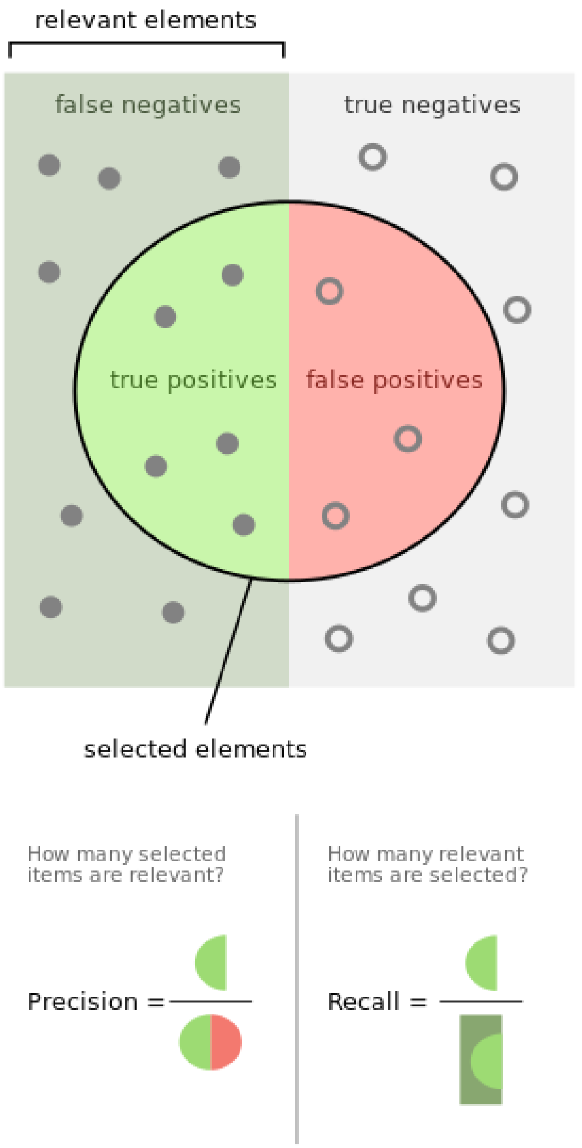
- Complex relation extraction: often no more than 60% f1 values, so even lower precision and recall!

*** first, do not harm**

# Use the Correct Quantitative Measurements

- Lack of precision leads to noise, too many false hits, too much work to review, which yields **high cost of review**.

- Lack of recall leads to missing relevant documents which yields **risk**.



# Should we instead use the accuracy measure for evaluation?

- Given a query, an engine classifies each doc as “Relevant” or “Nonrelevant”
- The **accuracy** of an engine: the fraction of these classifications that are correct
  - (tp + tn) / ( tp + fp + fn + tn)
- **Accuracy** is a commonly used evaluation measure in machine learning classification work
- Why is this not a very useful evaluation measure in IR?

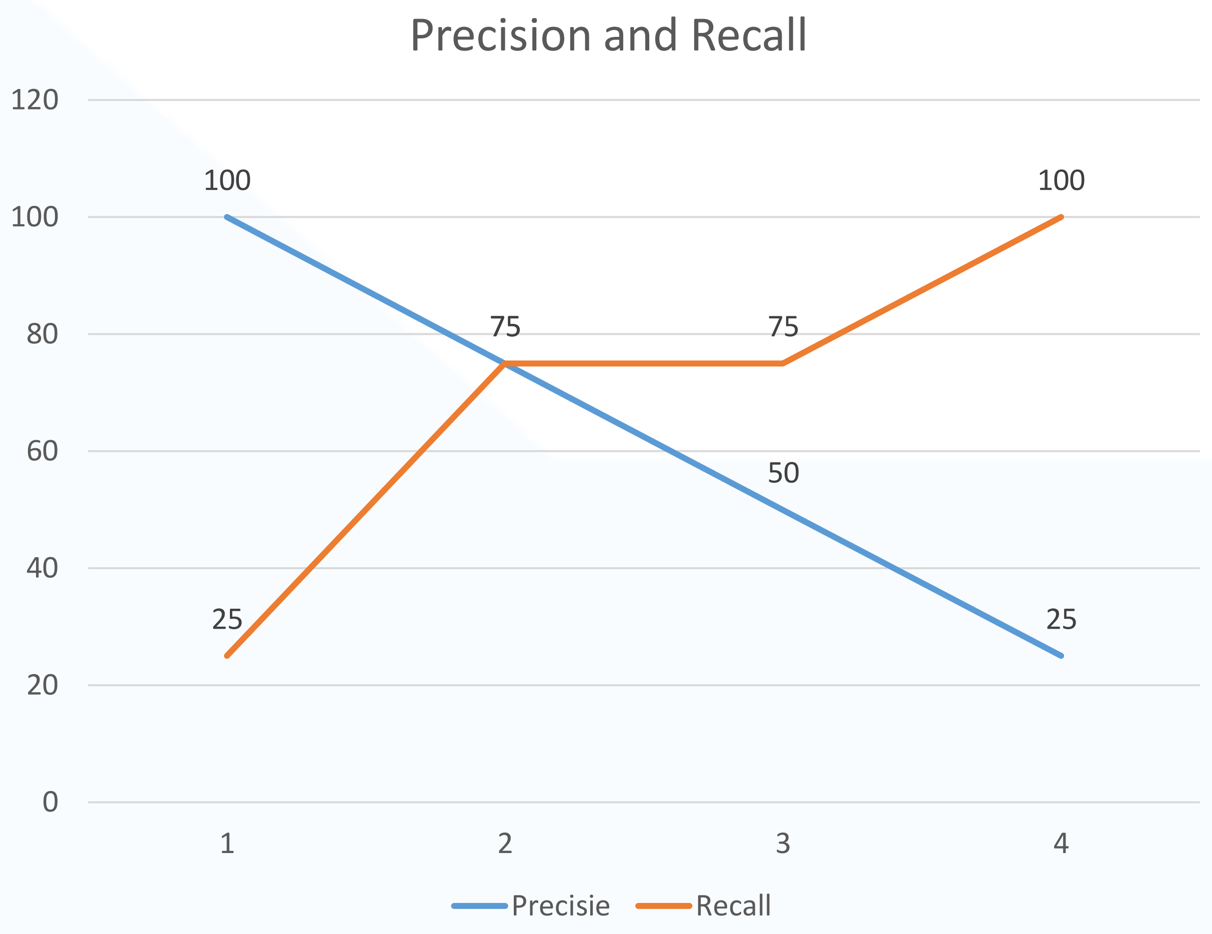
# High accuracy does not mean you find something useful

- How to build a 99.9999% accurate search engine on a low budget….
- Accuracy = (tp + tn) / ( tp + fp + fn + tn)


- Suppose we have 100.000 docs, we find 1 of them, there are 1000 relevant. Then accuracy = 1 + 99000 / 1 + 0 + 999 + 99000) = 99%. But we missed 999 documents!

# Precision & recall: reverse proportional

- Increase precision: AND, W/5, NOT
- Increase recall: OR, *, ?, Thesaurus, fuzzy.
- Both (up to certain level): Quorum search



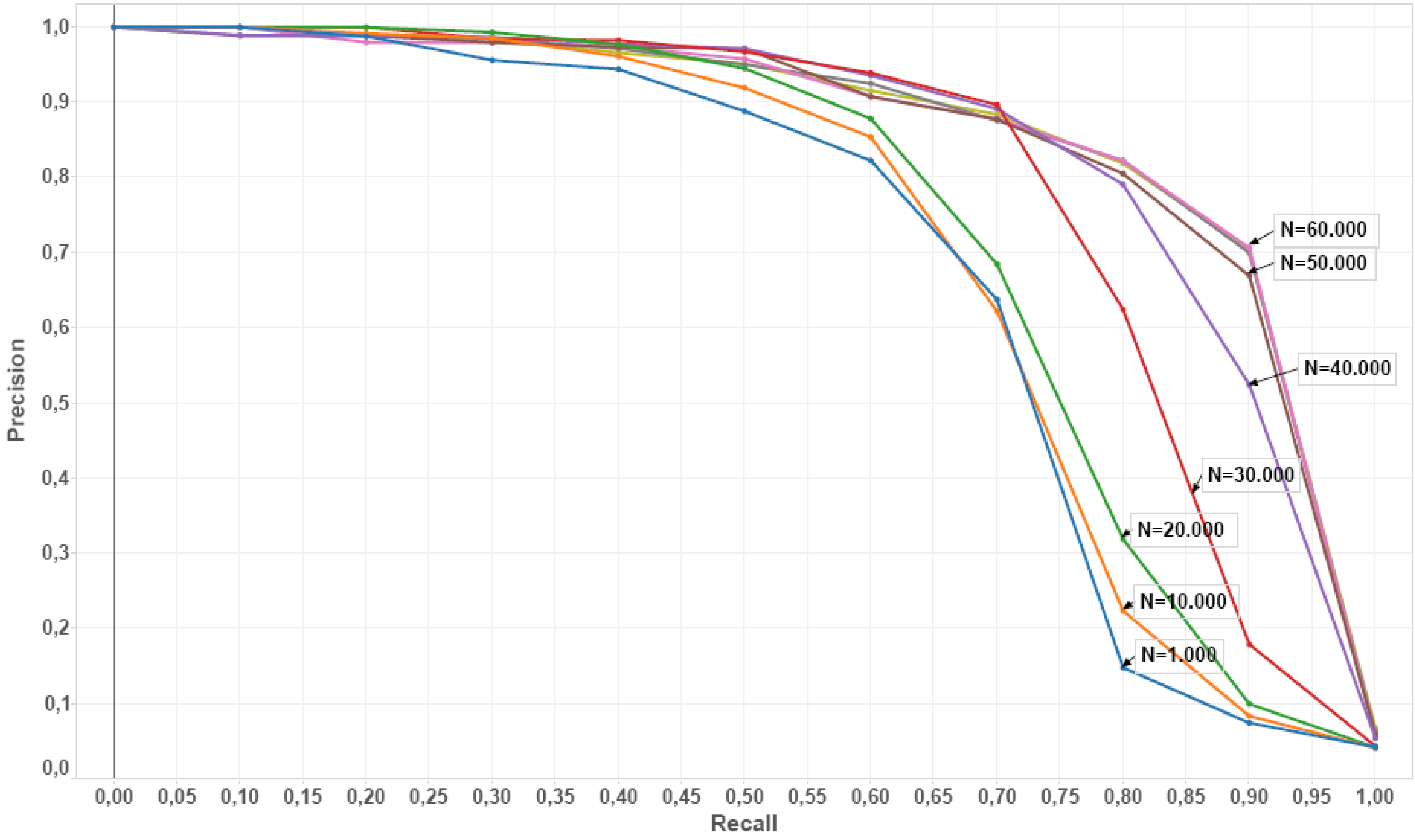



Figure 8.2: Precision-Recall curves of classifiers of various iterations on the evaluation set - Simulation of CAL protocol on the whole RCV1 corpus with topic code `GVIO`

# A combined measure: *F*

- Combined measure that assesses precision/recall tradeoff is **F measure**:

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

# Human Performance

- When both precision and recall are over 80%, human performance is approached.

- This applies to the best humans.

- It can be argued that values over 80% are often subject to different interpretations and discussions.

# Human, machine or Machine & Human?

What we observe in the real world:

1. (Good) human f-1 values are 60-80%

2. The best algorithms typically reach 80-90%

3. By first having a computer do the heavy lifting and initial selection and then have human beings make the final call: 95+%!

# Implementation Requirements

# There are different types of Bias

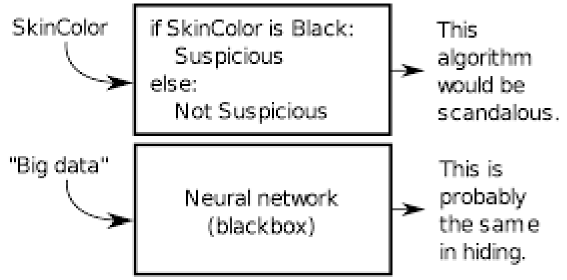
- Sample bias: the data used to train model does not accurately represent the real-world. Aka "balance" in training data. *Train car to drive only on day time images and not on night images.*

- Prejudice bias: training data is influenced by cultural stereotypes. *Images of people at work. Men are coding software, women are in kitchen cooking. Aka selection bias or confirmation bias*

- Measurement bias: systematic value distortion due to issues with the device used to measure features. *Using special filters on camera when taking pictures. Images without these filters will have lower recognition.*

- Algorithm bias: wrong algorithm. Wrong bias-variance balance. *Linear one that cannot deal with non-linear data.*

# Examples of Prejudice Bias


# Machine Learning: Variance and Bias

- Bias (error): The bias error is an *error from erroneous assumptions* in the learning algorithm. High bias can cause an algorithm to miss the relevant relations between features and target outputs (high bias leads to under fitting).

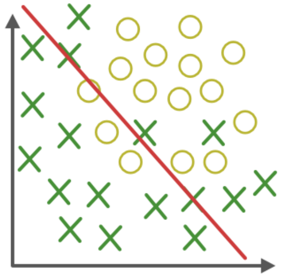
- Variance: The variance is an *error from sensitivity to small fluctuations in the training set*. High variance can cause an algorithm to model the random noise in the training data, rather than the intended outputs (high variance leads to overfitting)

*Source: https://en.wikipedia.org/wiki/Bias–variance_tradeoff*

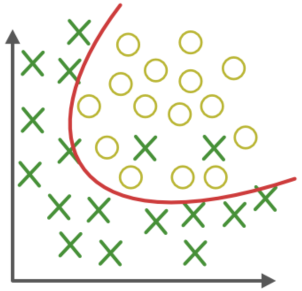
# Machine Learning

- Underfitting: occurs when a statistical model or machine learning algorithm cannot adequately capture the underlying structure of the data. It occurs when the model or algorithm does not fit the data enough. Caused by low variance but high bias.

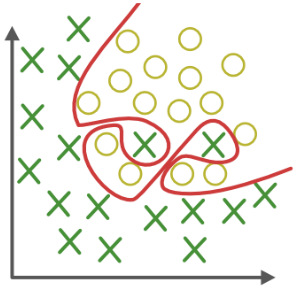
- Overfitting: “the production of an analysis that corresponds too closely or exactly to a particular set of data, and may therefore fail to fit additional data or predict future observations reliably”. Caused by high variance and low bias. Green line on right.



**Under-fitting**
(too simple to explain the variance)

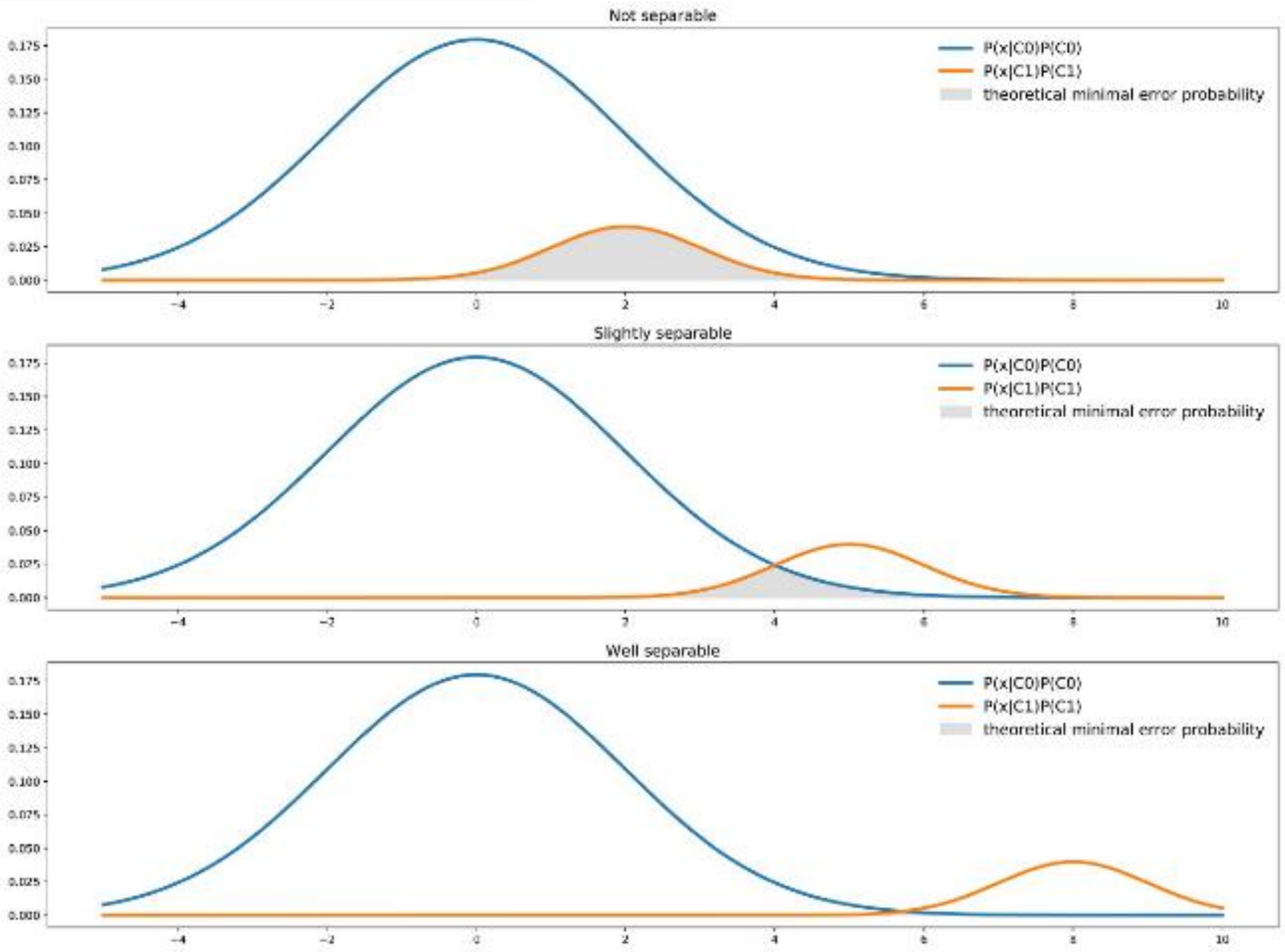


**Appropirate-fitting**

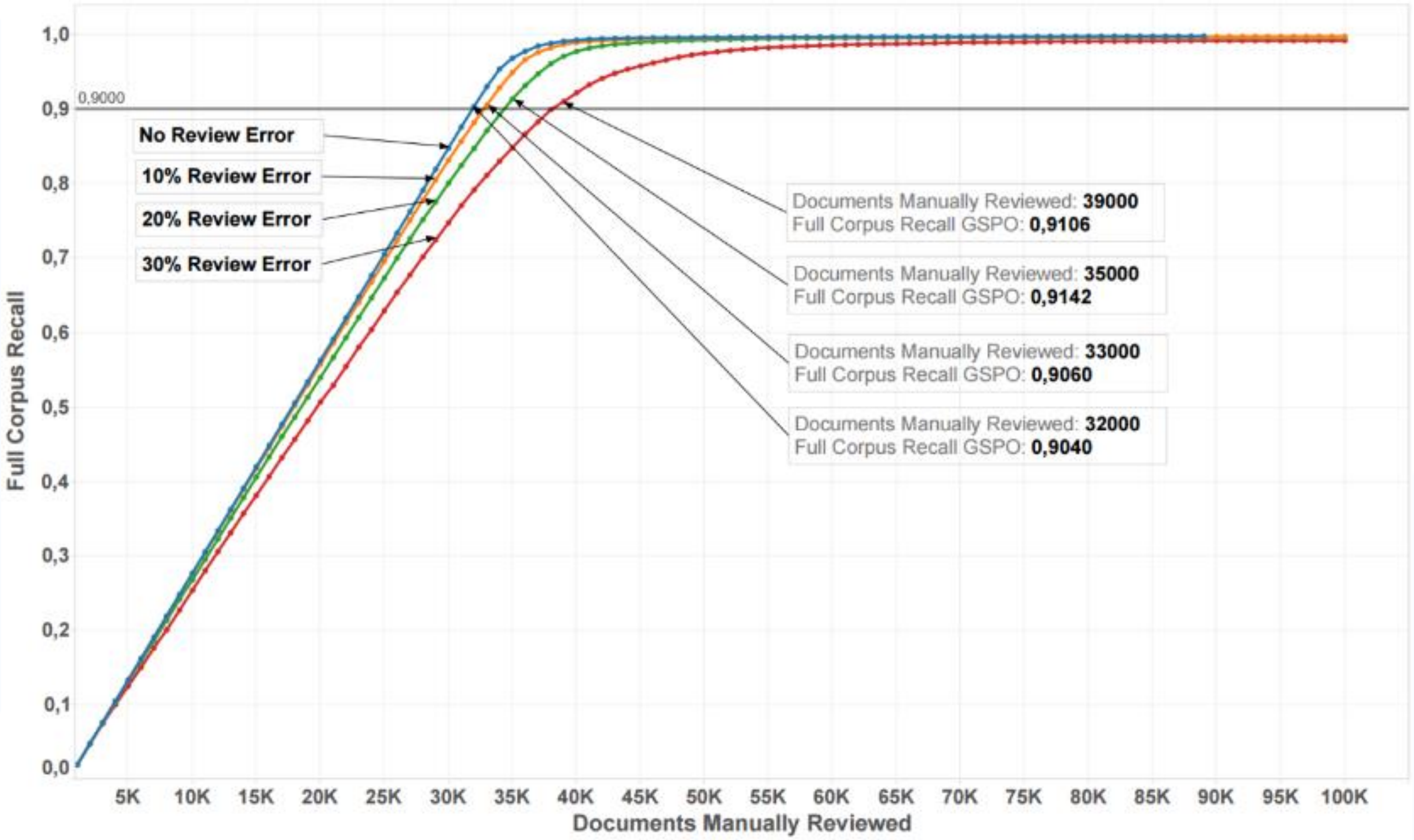


**Over-fitting**
(forcefitting--too good to be true)

# Imbalanced Training Data



# Robustness of your algorithms: test it extensively on noisy and incorrect data!



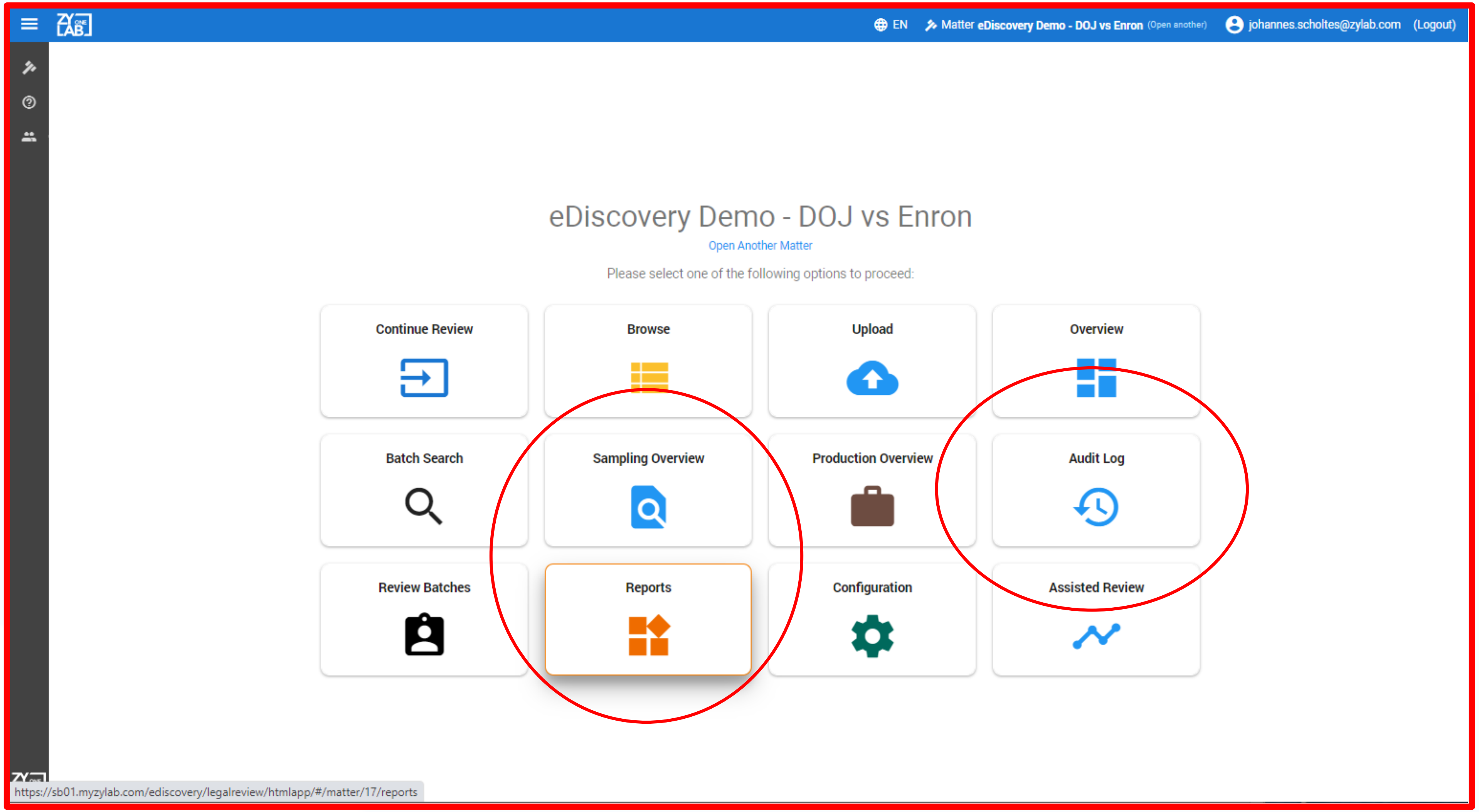
# Reproducibility of your technology

- Using the same algorithm on the same data should get you the same results, also at a later moment in time, regardless form where you run the algorithm.

→ *<u>Question</u>: Is the use of Google as a legal search engine defensible when it is used top identify relevant case law?*

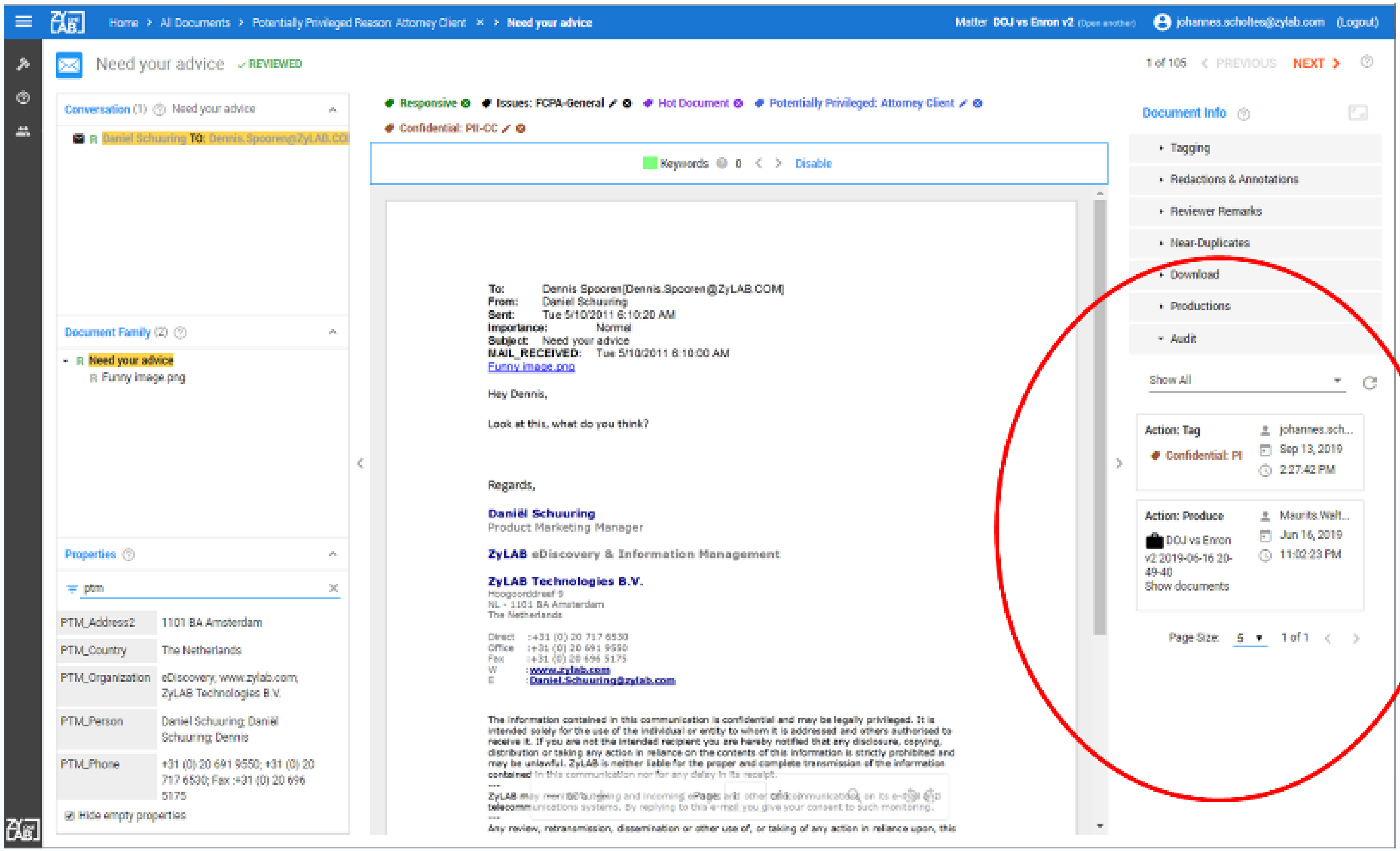
# Usage (Forensic) Requirements

# Legally Defensible Users: Reporting, Sampling & Audit logs



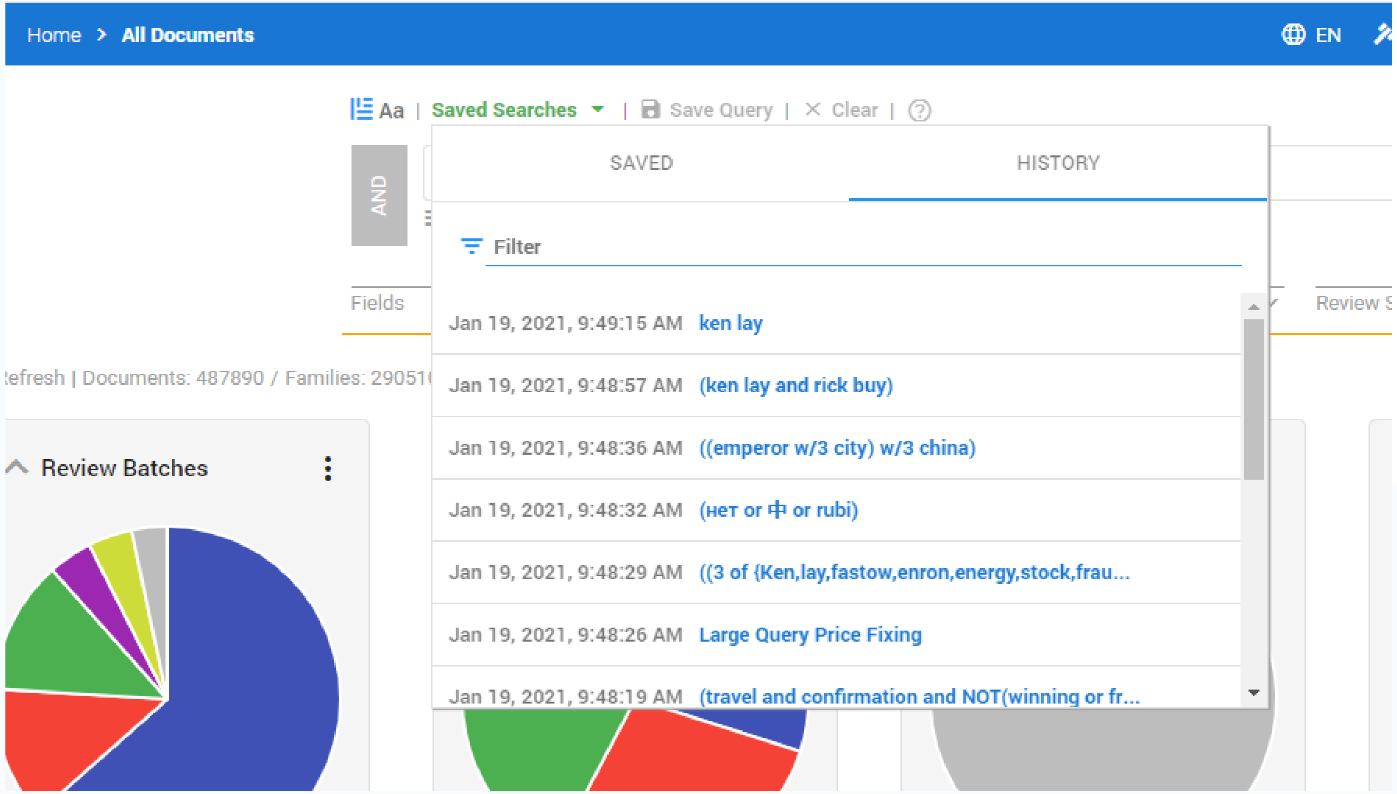
# Documentation: *Chain of Custody* (Who did what when?)

- Search logs
- Audit logs
- Reporting
- Inclusion reports
- Exclusion reports
- …



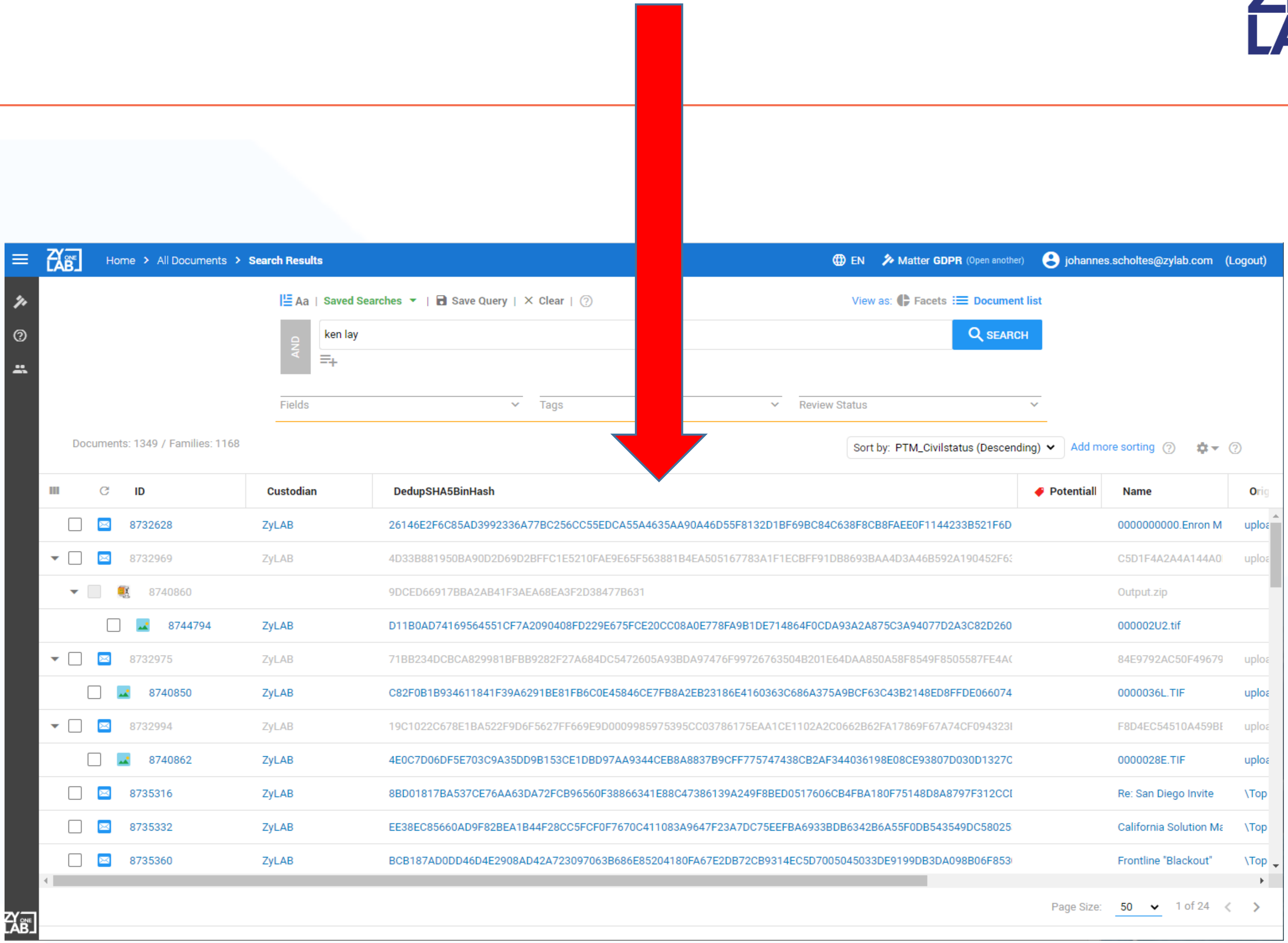
# Search logs: evidence and falsification

- Keep track of previous queries and results.
- Document that one searches both for evidence, but also for potential falsifications.
- Avoid tunnel vision.



# Forensic Integrity

- Hashing at collection
- Multiple purpose:
  - De-duplication
  - Preservation of forensic integrity by uniquely storing evidence of non-changed content of file

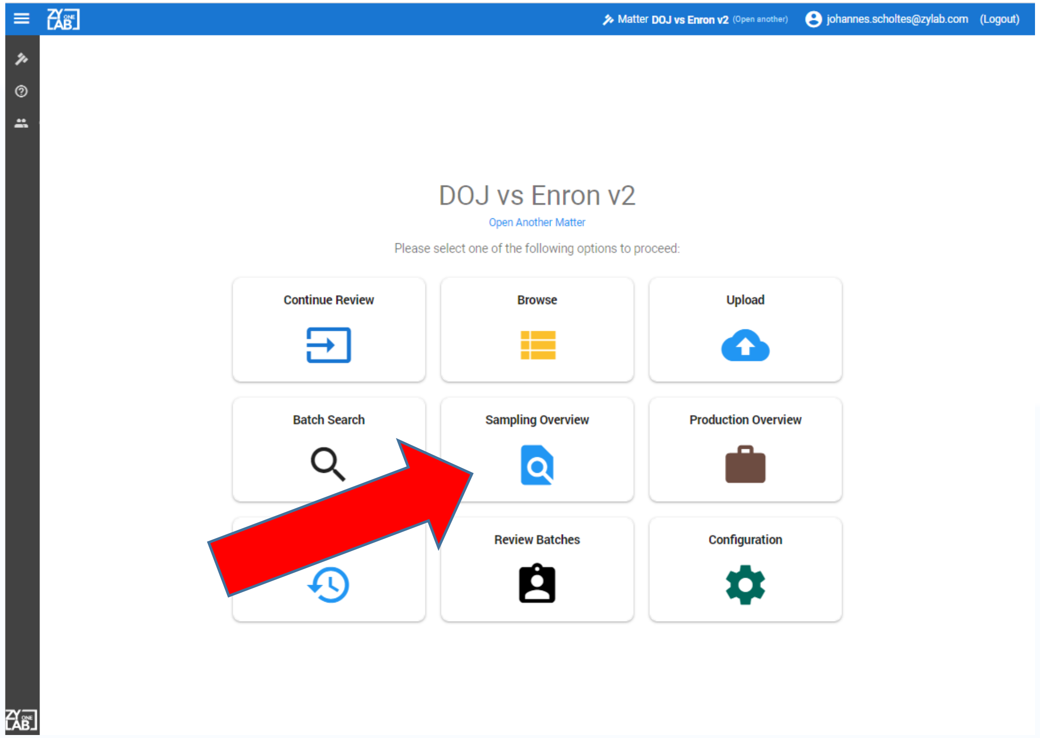


# Quality Control by using sampling

- **Test** the results of all **automatic processes** always manually on a random sample.

- This is the most reliable way to explain laymen the working of a complex algorithm and gain trust.

- Alternative are expert witnesses.



# Using sampling

1. Whenever using any kind of automatic (AI) process
2. Select the documents on which the process has been applied
3. Create a random sample of X % (subject of negotiations and risk), typically X = 2-5% on large data sets(>1000) to 10%-50% on small data sets. There are statistical models that can provide guidance on exact measurements.
4. Review this set and keep track of maximum obtainable quality.
5. When the quality drops below a certain threshold: go back to #1 and adjust the parameters of your automatic process. Address most common errors.
6. Continue until the quality random sample is above the set quality threshold.

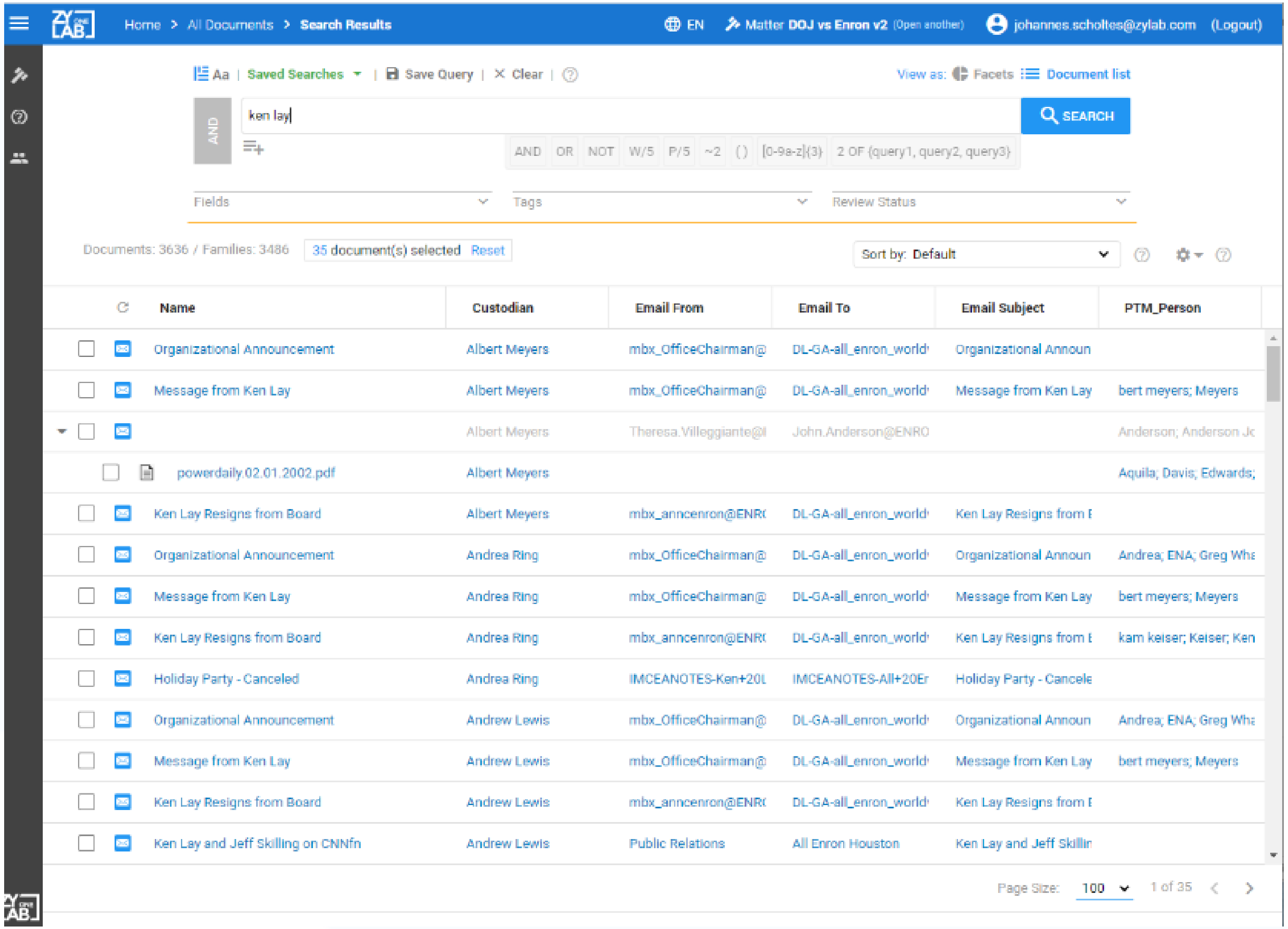
# How large should your sample be?

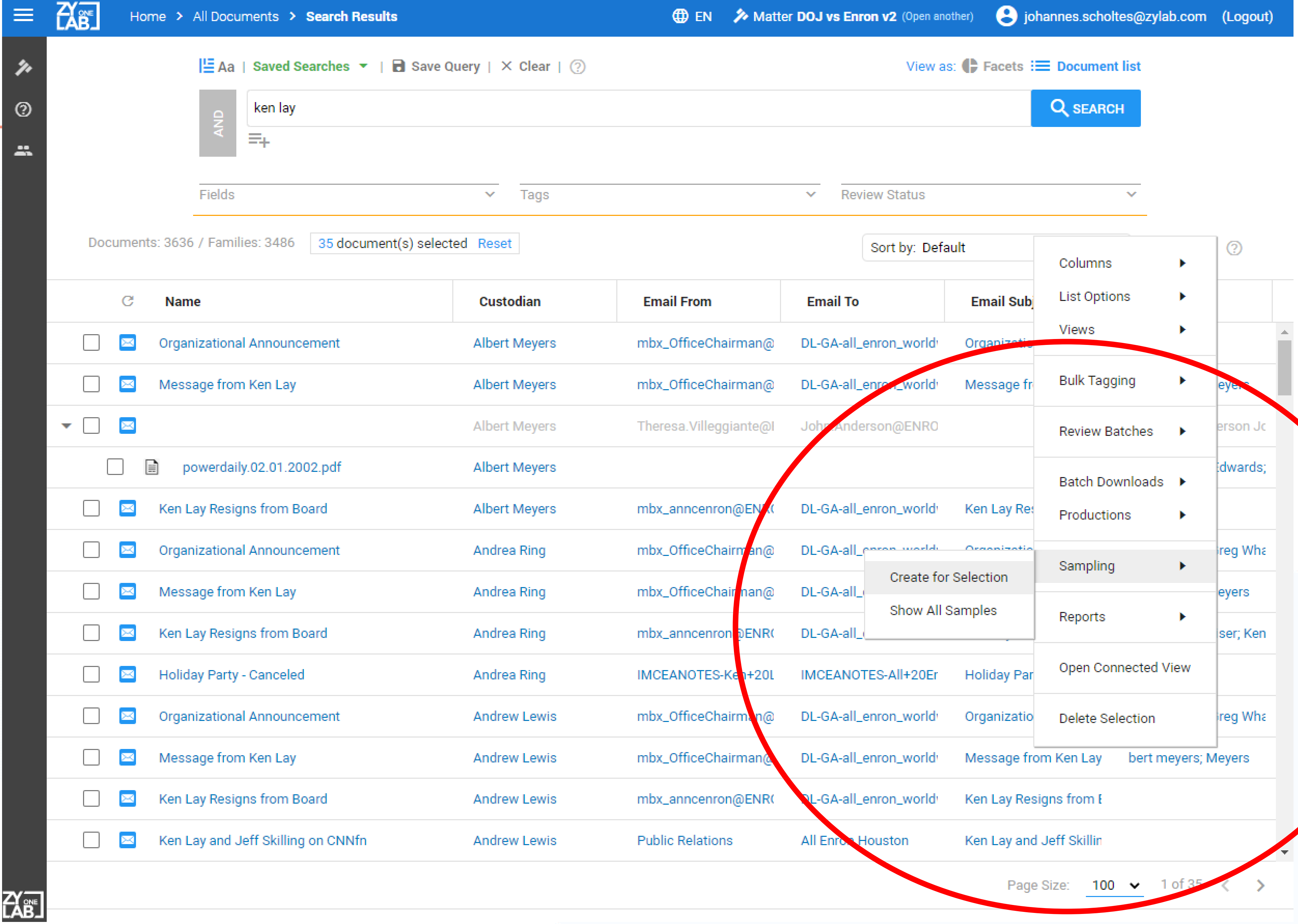
**Raosoft®** — **Sample size calculator**

| | | |
|---|---|---|
| What margin of error can you accept?<br>5% is a common choice | 5 % | The margin of error is the amount of error that you can tolerate. If 90% of respondents answer *yes*, while 10% answer *no*, you may be able to tolerate a larger amount of error than if the respondents are split 50-50 or 45-55.<br>Lower margin of error requires a larger sample size. |
| What confidence level do you need?<br>Typical choices are 90%, 95%, or 99% | 95 % | The confidence level is the amount of uncertainty you can tolerate. Suppose that you have 20 yes-no questions in your survey. With a confidence level of 95%, you would expect that for one of the questions (1 in 20), the percentage of people who answer *yes* would be more than the margin of error away from the true answer. The true answer is the percentage you would get if you exhaustively interviewed everyone.<br>Higher confidence level requires a larger sample size. |
| What is the population size?<br>If you don't know, use 20000 | 20000 | How many people are there to choose your random sample from? The sample size doesn't change much for populations larger than 20,000. |
| What is the response distribution?<br>Leave this as 50% | 50 % | For each question, what do you expect the results will be? If the sample is skewed highly one way or the other,the population probably is, too. If you don't know, use 50%, which gives the largest sample size. See below under **More information** if this is confusing. |
| Your recommended sample size is | 377 | This is the minimum recommended size of your survey. If you create a sample of this many people and get responses from everyone, you're more likely to get a correct answer than you would from a large sample where only a small percentage of the sample responds to your survey. |

*http://www.raosoft.com/samplesize.html*

# Select document for Quality control

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johannes.scholtes@zylab.com (Logout)
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Tags
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Documents: 3636 / Families: 3486
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Message from Ken Lay | Albert Meyers | mbx_OfficeChairman@ | DL-GA-all_enron_world
Albert Meyers | Theresa.Villeggiante@ | John.Anderson@ENRO
powerdaily.02.01.2002.pdf | Albert Meyers
Ken Lay Resigns from Board | Albert Meyers | mbx_anncenron@EN | DL-GA-all_enron_world
Organizational Announcement | Andrea Ring
Message from Ken Lay | Andrea Ring
Ken Lay Resigns from Board | Andrea Ring
Holiday Party - Canceled | Andrea Ring | IMCEANOTES-Ken+20L | IMCEANOTES-All+20Er | Holiday Par
Organizational Announcement | Andrew Lewis | mbx_OfficeChairman@ | DL-GA-all_enron_world | Organizatio
Message from Ken Lay | Andrew Lewis | mbx_OfficeChairman@ | DL-GA-all_enron_world | Message from Ken Lay | bert meyers; Meyers
Ken Lay Resigns from Board | Andrew Lewis | mbx_anncenron@ENR | DL-GA-all_enron_world | Ken Lay Resigns from E
Ken Lay and Jeff Skilling on CNNfn | Andrew Lewis | Public Relations | All Enron Houston | Ken Lay and Jeff Skillir
Columns
List Options
Views
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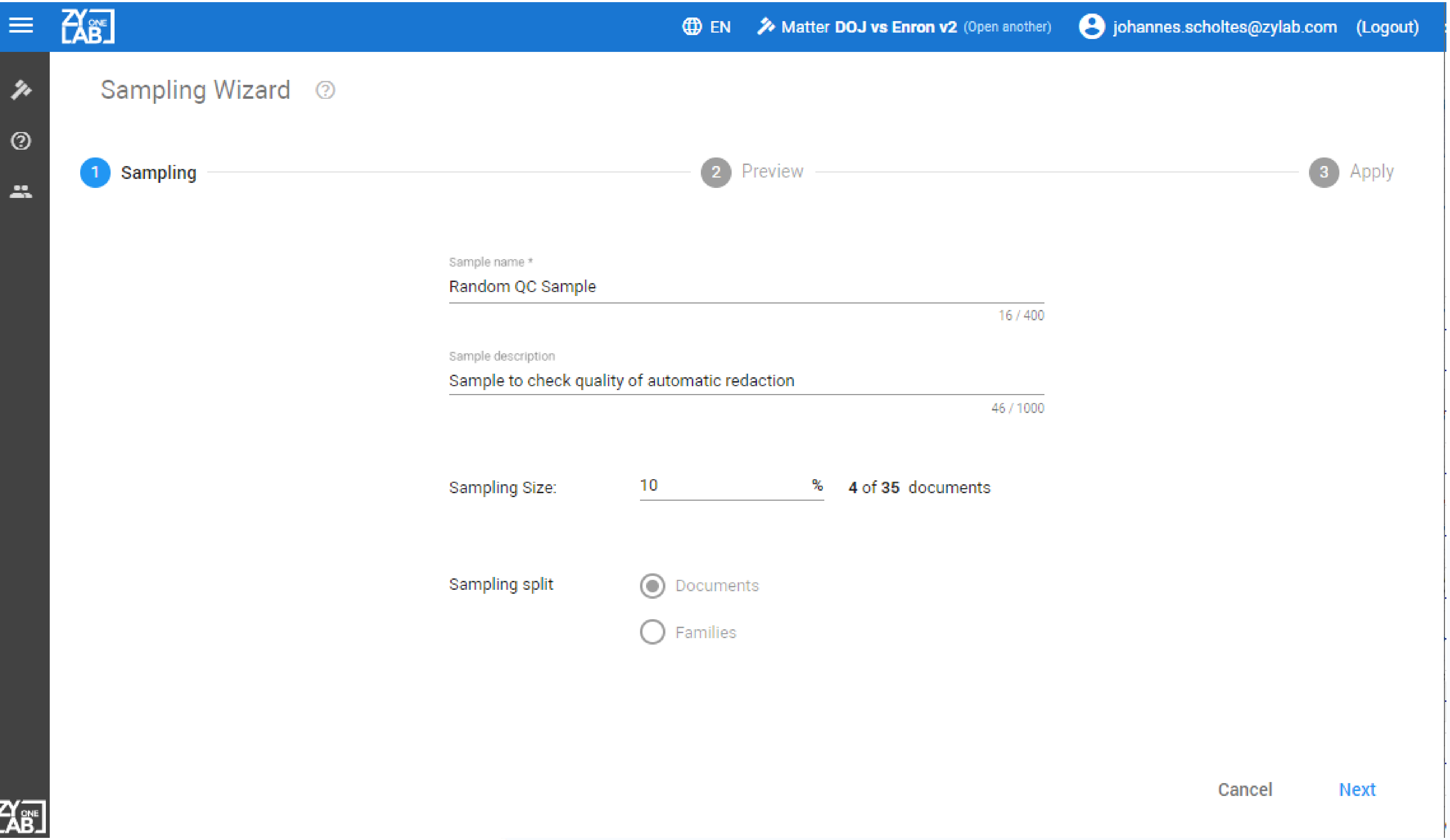
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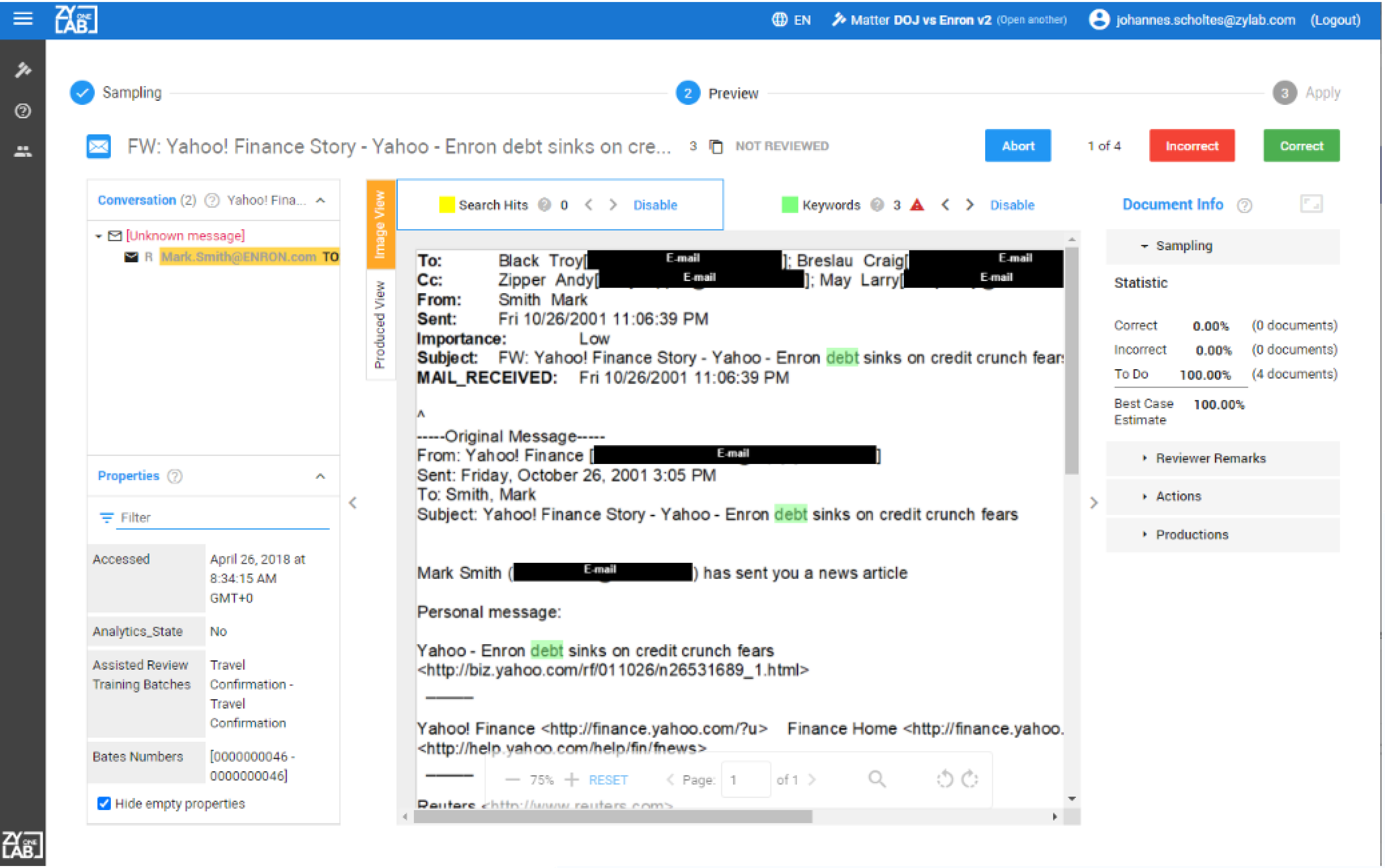
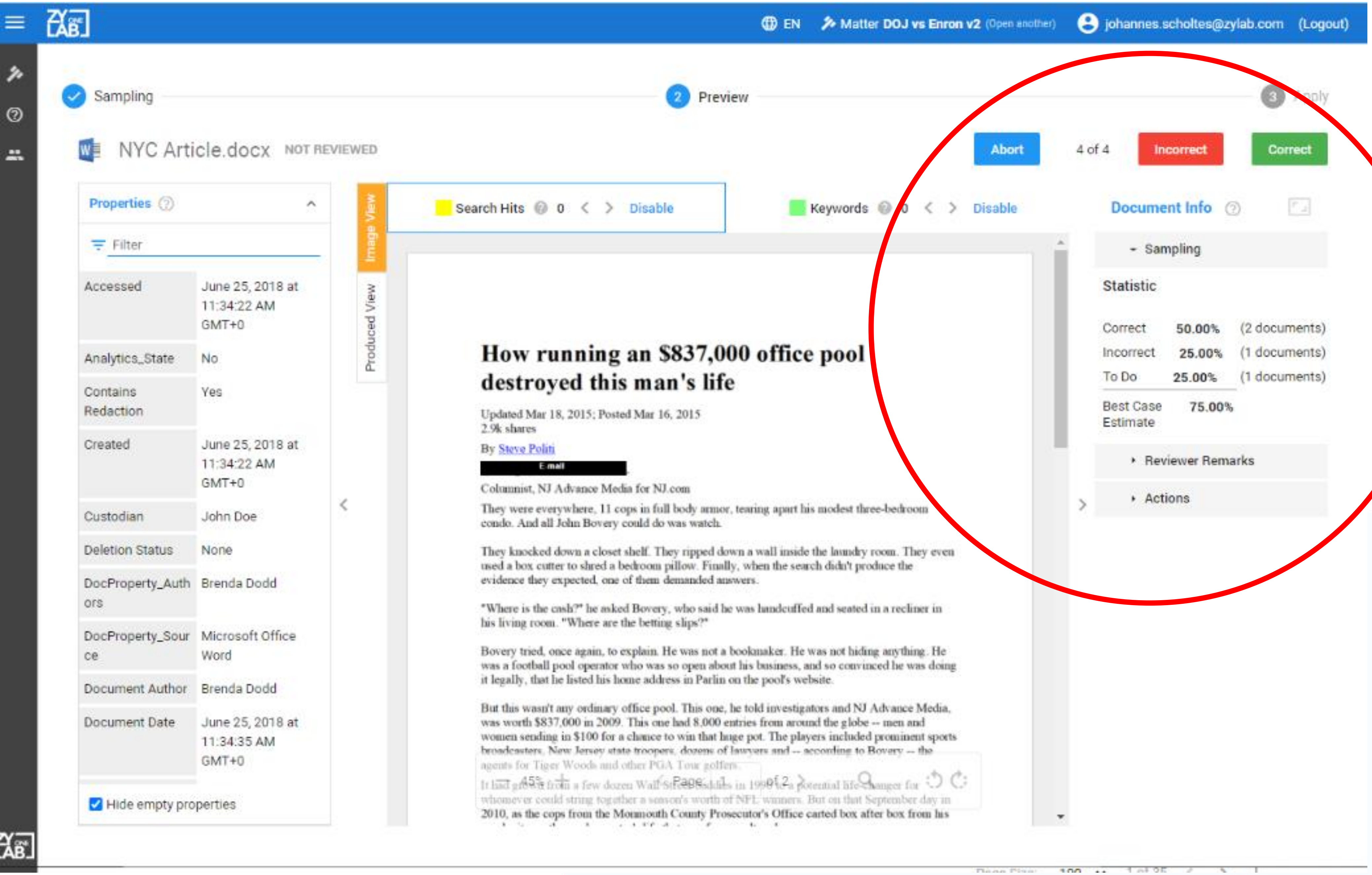
Matter DOJ vs Enron v2 (Open another)
johannes.scholtes@zylab.com (Logout)
Sampling Wizard
1 Sampling
2 Preview
3 Apply
Sample name *
Random QC Sample
16 / 400
Sample description
Sample to check quality of automatic redaction
46 / 1000
Sampling Size:
10 %
4 of 35 documents
Sampling split
Documents
Families
Cancel
Next


EN
Matter DOJ vs Enron v2 (Open another)
johannes.scholtes@zylab.com (Logout)
Sampling
2 Preview
3 Apply
FW: Yahoo! Finance Story - Yahoo - Enron debt sinks on cre...
3
NOT REVIEWED
Abort
1 of 4
Incorrect
Correct
Conversation (2) Yahoo! Fina...
[Unknown message]
R Mark.Smith@ENRON.com TO
Image View
Produced View
Search Hits 0 Disable
Keywords 3 Disable
Document Info
To: Black Troy[[redacted]]; Breslau Craig[[redacted]
Cc: Zipper Andy[[redacted]]; May Larry[[redacted]
From: Smith Mark
Sent: Fri 10/26/2001 11:06:39 PM
Importance: Low
Subject: FW: Yahoo! Finance Story - Yahoo - Enron debt sinks on credit crunch fear
MAIL_RECEIVED: Fri 10/26/2001 11:06:39 PM
^
-----Original Message-----
From: Yahoo! Finance [[redacted]]
Sent: Friday, October 26, 2001 3:05 PM
To: Smith, Mark
Subject: Yahoo! Finance Story - Yahoo - Enron debt sinks on credit crunch fears
Mark Smith ([redacted]) has sent you a news article
Personal message:
Yahoo - Enron debt sinks on credit crunch fears
<http://biz.yahoo.com/rf/011026/n26531689_1.html>
Yahoo! Finance <http://finance.yahoo.com/?u> Finance Home <http://finance.yahoo.
<http://help.yahoo.com/help/fin/fnews>
75% RESET Page: 1 of 1
Sampling
Statistic
Correct 0.00% (0 documents)
Incorrect 0.00% (0 documents)
To Do 100.00% (4 documents)
Best Case Estimate 100.00%
Reviewer Remarks
Actions
Productions
Properties
Filter
Accessed April 26, 2018 at 8:34:15 AM GMT+0
Analytics_State No
Assisted Review Training Batches Travel Confirmation - Travel Confirmation
Bates Numbers [0000000046 - 0000000046]
Hide empty properties


EN
Matter DOJ vs Enron v2 (Open another)
johannes.scholtes@zylab.com (Logout)
Sampling
2 Preview
3 Apply
NYC Article.docx NOT REVIEWED
Abort
4 of 4
Incorrect
Correct
Properties
Filter
Accessed June 25, 2018 at 11:34:22 AM GMT+0
Analytics_State No
Contains Redaction Yes
Created June 25, 2018 at 11:34:22 AM GMT+0
Custodian John Doe
Deletion Status None
DocProperty_Authors Brenda Dodd
DocProperty_Source Microsoft Office Word
Document Author Brenda Dodd
Document Date June 25, 2018 at 11:34:35 AM GMT+0
Hide empty properties
Image View
Produced View
Search Hits 0 Disable
Keywords 0 Disable
How running an $837,000 office pool destroyed this man's life
Updated Mar 18, 2015; Posted Mar 16, 2015
2.9k shares
By Steve Politi
E-mail
Columnist, NJ Advance Media for NJ.com
They were everywhere, 11 cops in full body armor, tearing apart his modest three-bedroom condo. And all John Bovery could do was watch.
They knocked down a closet shelf. They ripped down a wall inside the laundry room. They even used a box cutter to shred a bedroom pillow. Finally, when the search didn't produce the evidence they expected, one of them demanded answers.
"Where is the cash?" he asked Bovery, who said he was handcuffed and seated in a recliner in his living room. "Where are the betting slips?"
Bovery tried, once again, to explain. He was not a bookmaker. He was not hiding anything. He was a football pool operator who was so open about his business, and so convinced he was doing it legally, that he listed his home address in Parlin on the pool's website.
But this wasn't any ordinary office pool. This one, he told investigators and NJ Advance Media, was worth $837,000 in 2009. This one had 8,000 entries from around the globe -- men and women sending in $100 for a chance to win that huge pot. The players included prominent sports broadcasters, New Jersey state troopers, dozens of lawyers and -- according to Bovery -- the agents for Tiger Woods and other PGA Tour golfers.
Document Info
Sampling
Statistic
Correct 50.00% (2 documents)
Incorrect 25.00% (1 documents)
To Do 25.00% (1 documents)
Best Case Estimate 75.00%
Reviewer Remarks
Actions

# Q&A

Thank you