3rd MLFPM Summer School

A practical guide to information extraction from medical texts

Sven Laur
University of Tartu

Why information extraction is needed

Electronic health records are mostly unstructured:

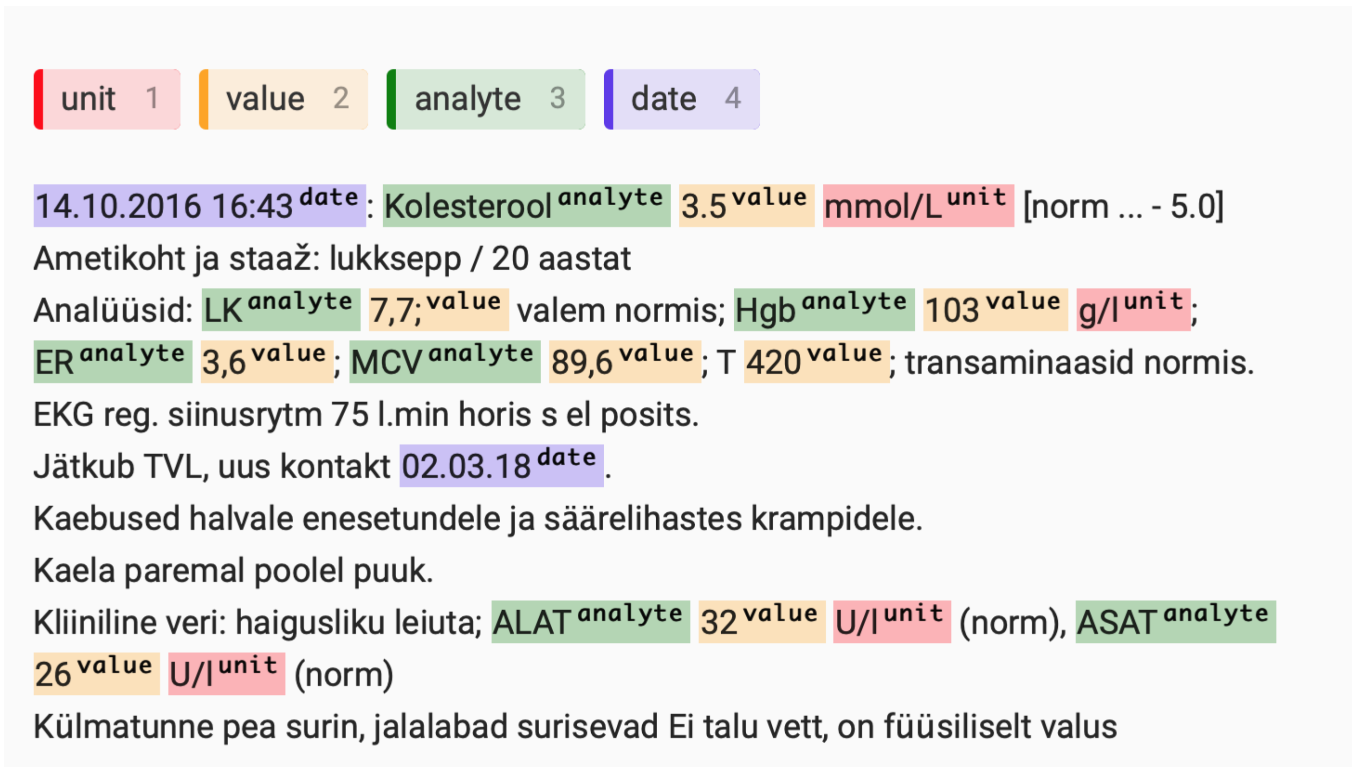
- ◇ patient complaints (adverse drug reactions)
- ◇ disease descriptions are textual (deep phenotyping)
- ◇ biopsies have textual descriptions (cancer studies)
- ◇ descriptions of X-ray scans are textual (label assignment)

Information extraction allows us:

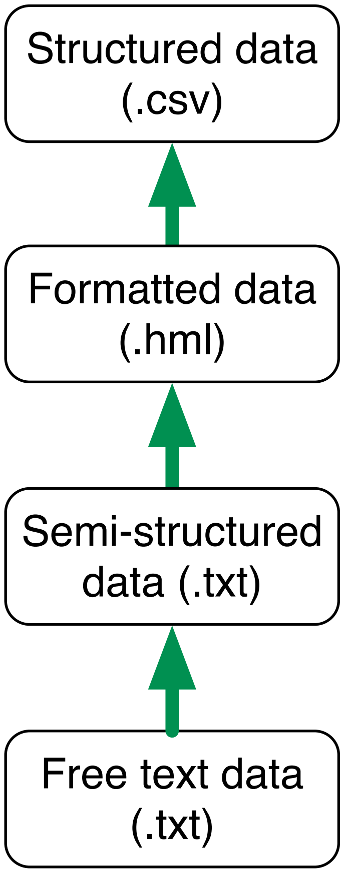
- ◇ to fill gaps in the structured data (allergies)
- ◇ to describe environment factors (lifestyle and family history)
- ◇ to refine diagnosis description (infraction subtypes)
- ◇ to refined treatment outcomes (stroke complications)

Example. Measurement extraction

Extract dated lab measurements from a patient health record.



NLP tasks in medical domain



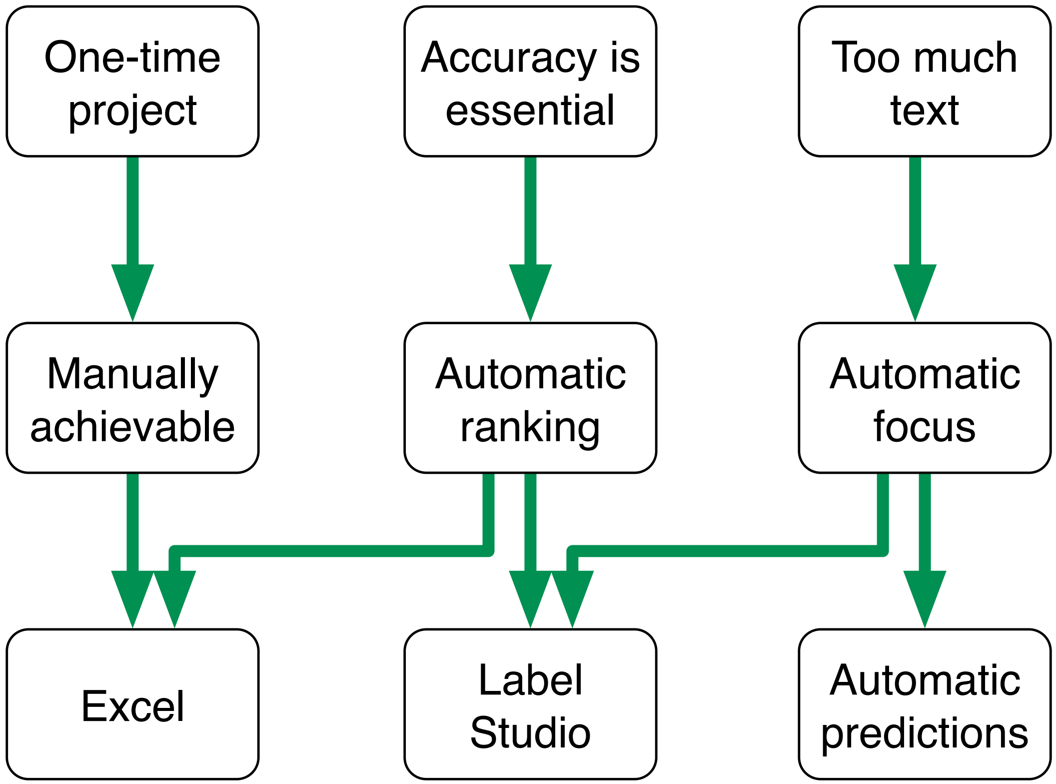
- Cleaning individual values (1, 3 $\rightsquigarrow$ 1.3)
- Standardisation of terms (penicillin $\rightsquigarrow$ J01C)
- Harmonisation and conflict resolution

- Extraction of individual data fields
- Unification of different data formats

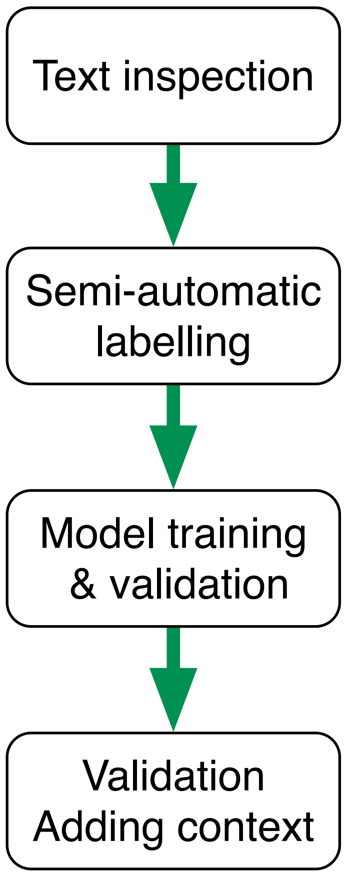
- Format discovery
- Robust parsing
- Text segmentation

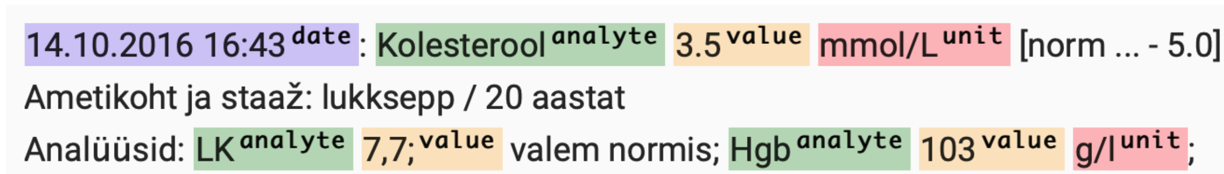
- Text segmentation
- Relevance ranking
- Fact extraction

How to carry out information extraction



Typical steps for a fact extraction task



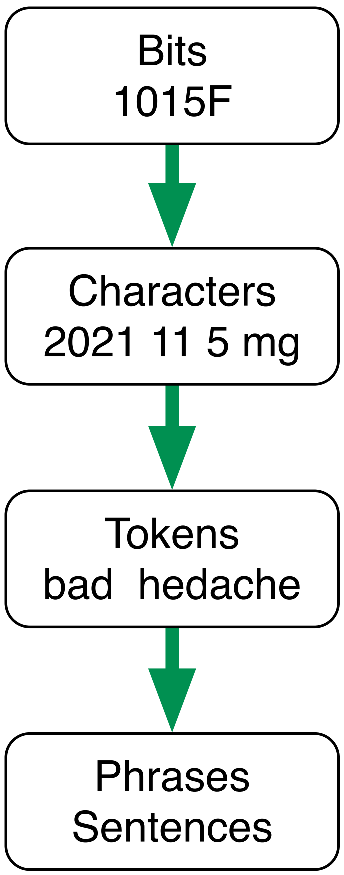


- ▷ Term lists and regular expressions
- ▷ Text segmentation and focus regions
- ▷ Dataset enrichment. Manual corrections

- ▷ Detection and extraction tasks
- ▷ Text prioritisation task

- ▷ Plausibility (Weight: 1.63 kg)
- ▷ Context (Weight: 3.4 kg 30 year female)

Abstraction levels in text mining



- ▷ Charset detection (utf-8, Latin-1, Windows-1257)
- ▷ Recovery from encoding errors (jΓjriΓ¶Γ¶ ⇝ jüriöö)

Tokenisation

- ▷ number and abbrevation detection (weight 1, 3 kg)
- ▷ word normalisation (hedache⇝headache, ug⇝ μg)

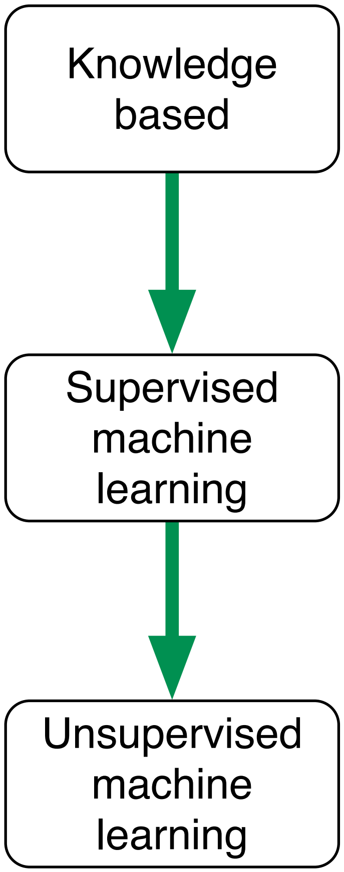
Token-level annotations

- ▷ morphological analysis (cramped ⇝ verb, past tense)
- ▷ term ontologies (penicillin ⇝ J01C, liver ⇝ abdomen)

Phrase level analysis

- ▷ text segmentation and relevance ranking (focus)
- ▷ fact extraction and text quantification (prediction)

Commonly used methods



Rule-based methods

- ▷ term lists
- ▷ regular expressions & rewriters
- ▷ phrase grammars

Lexicons
Ontologies
Standards

Supervised machine learning

- ▷ text segmentation
- ▷ text classification
- ▷ keyword assignment

Text annotations

CPU & GPU time

Unsupervised machine learning

- ▷ word embeddings (WORD2VEC)
- ▷ transformers (BERT & GPT-3)
- ▷ similarity scoring (WMD)

Unlabelled text

Few text annotations

CPU & GPU time

Rule-based methods

Standards as the source of term lists

Disease names

◇ ICD-10, SNOMED-CT

Lab measurements

◇ LOINC, SNOMED-CT

Drug names and adverse reactions

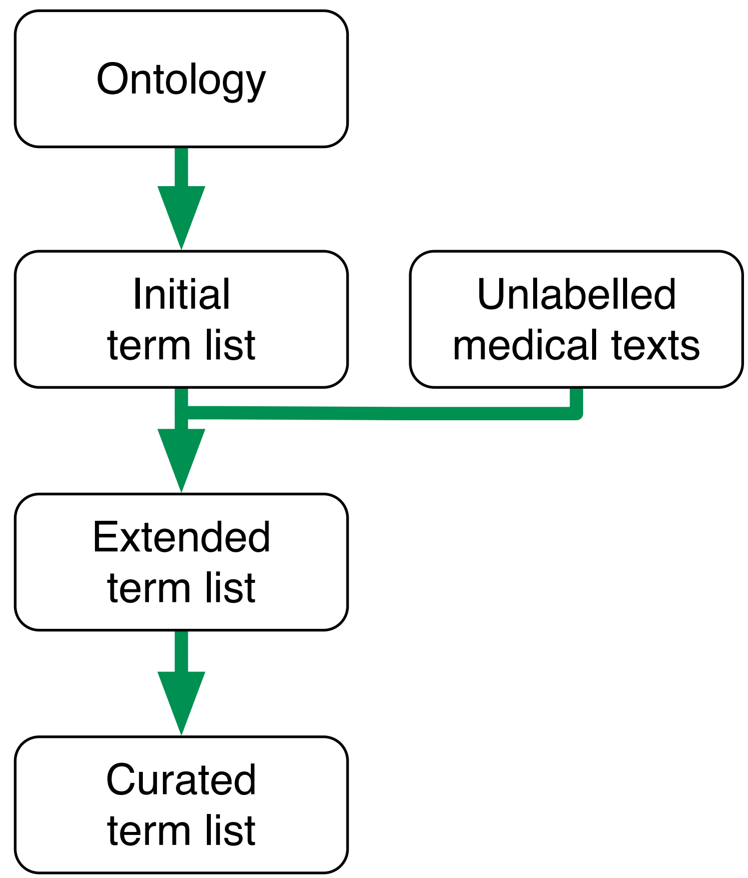
◇ ATC, SNOMED-CT

◇ drug package leaflets

Anatomy

◇ AEO, CARO, SNOMED-CT

◇ medical dictionaries



Tokenisation with regular expressions

Regular expression is a way to specify tokens with fixed structure:

- ▷ dates (`[0-9]^2.[0-9]^2.[0-9]^4`)
- ▷ number formats (`-?[0-9]^+.[0-9]^+`)
- ▷ special symbols, headers

Do **not** use regular expression for predictable variations in term lists.

- ▷ handling long term lists is much more efficient.
- ▷ you might get `a|ab|abc` vs `abc|ab|a` problems.

Software development practices:

- ▷ Write test cases for each surprise.
- ▷ Maintain common library of regular expressions.

What is a phrase grammar

A phrase grammar is a list of rules that combines tokens into phrases:

$$\textsc{Number Unit} \rightsquigarrow \textsc{QNumber}$$
$$\textsc{Date Analyte QNumber} \rightsquigarrow \textsc{Measurement}$$
$$\textsc{Analyte QNumber} \rightsquigarrow \textsc{Measurement}$$
$$\textsc{Date Analyte Number} \rightsquigarrow \textsc{Measurement}$$
$$\textsc{Analyte Number} \rightsquigarrow \textsc{Measurement}$$

- ▷ There can be several phrase symbols of interest.
- ▷ If many rules apply the one with highest priority is applied.
- ▷ Rules can specify how to compute extra attributes for derived symbols.
- ▷ All phrase grammars classes are finite in practice.

Illustrative example

Canonical phrase

`21.05.2021` `Cholesterol` `100.2` `mg/dL`

$$\rightsquigarrow$$

$$\textsc{Measurement}(date = 2021/05/21, analyte = Cholesterol, \ldots)$$

Incomplete phrases we must match

- `Cholesterol` `100.2` `mg/dL`
- `21.05.2021` `Cholesterol` `100.2`
- `Cholesterol` `100.2`

Advanced tricks

Incomplete phrases reveal missing knowledge

- ▷ `21.05.2021` `HDL` `20.3` `mg/dL`
- ▷ `21.05.2021` `Cholesterol` `406` `mg/L`

Additional checks

- ▷ `Last measurement of` `Cholesterol` `2005`

Tokenisation is ambiguous in practice

- ▷ `Cholesterol` `21.05 2021` `40.6` `;` `HDL`
- ▷ `Cholesterol` `21.05` `2021` `40.6 ;` `HDL`

Conclusion

Advantages of rule-based methods:

- ▷ Easy to achieve decent progress.
- ▷ Do not need extensive manual annotations.
- ▷ A good baseline for segmentation tasks.

Disadvantages of rule-based methods:

- ▷ Manual derivation of rules is hard.
- ▷ Curation of background information is hard.
- ▷ Progressively harder to improve the performance.

Supervised machine learning

Support Vector Machines

Linear classifier is an automatic way to derive implicit rules from examples

$$f(x) = 1 \times \boxed{\texttt{Cholesterol}}(x) + 1 \times \boxed{\texttt{HDL}}(x) + 1 \times \boxed{\texttt{LDL}}(x) - 2$$

$$\Updownarrow$$

$$\boxed{\texttt{Cholesterol}}(x) \wedge \boxed{\texttt{HDL}}(x) = \textsc{True}$$

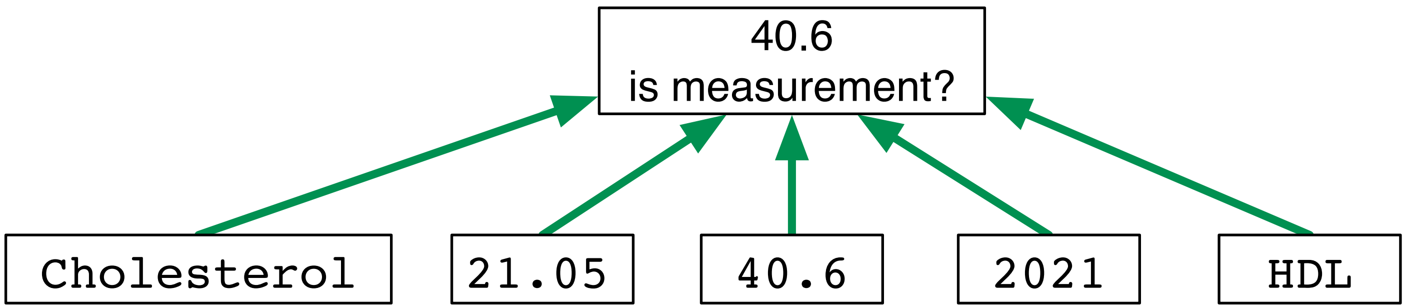
$$\boxed{\texttt{HDL}}(x) \wedge \boxed{\texttt{LDL}}(x) = \textsc{True}$$

$$\boxed{\texttt{Cholesterol}}(x) \wedge \boxed{\texttt{LDL}}(x) = \textsc{True}$$

Support Vector Machine is *statistically stable way* to do linear classification.

▷ Feature maps and kernels allow to do nonlinear combination of features.

Manual feature engineering



The quality of predictions mostly depends on available features:

▷ term lists

▷ phrase lists

▷ morphological features

▷ size of the window

Output smoothing with CRF

- The predictions of SVM are independent for each position.

`21.05` 2021 `Cholesterol` `40.6` ; `HDL` `16.3` `mg/dL`

- Consistency requirements can be modelled with Markov random fields.

very unlikely

- Conditional Random Fields smooths independent predictions.

`21.05` 2021 `Cholesterol` `40.6` ; `HDL` `16.3` `mg/dL`

`21.05` `2021` `Cholesterol` `40.6` ; `HDL` `16.3` `mg/dL`

Word embeddings

Word embedding defines 100-1000 informative features for each word.

▷ Features are defined automatically.
▷ Masked language modelling is used for training.
▷ Each word gets a fixed representation vector.
▷ Cosine similarity between embeddings indicates semantical closeness.

By running SVM on top of embeddings:

▷ We do not need to hand-crafting word-based features.
▷ We still have to think about the window size.
▷ We have to fix the amount of unknown words.
▷ We ignore that words can have multiple meanings.

Context sensitive word embeddings

Neural networks define informative features for each occurrence of the word.

- ▷ Features are defined automatically.
- ▷ Masked language modelling is used for training.
- ▷ There is no observation window – information can flow.
- ▷ Different meanings of the words get different representations.
- ▷ Sentences or paragraphs get also representations.

By running a neural network on top of context-sensitive embeddings:

- ▷ We can adjust the baseline representation for current task.
- ▷ We still cannot capture dark background knowledge.

Iterative improvement

Three main sources of improvement

Improve the quality of term lists and ontologies.

▷ Use version control smartly to communicate changes

Extraction quality does not increase if you do not measure it!

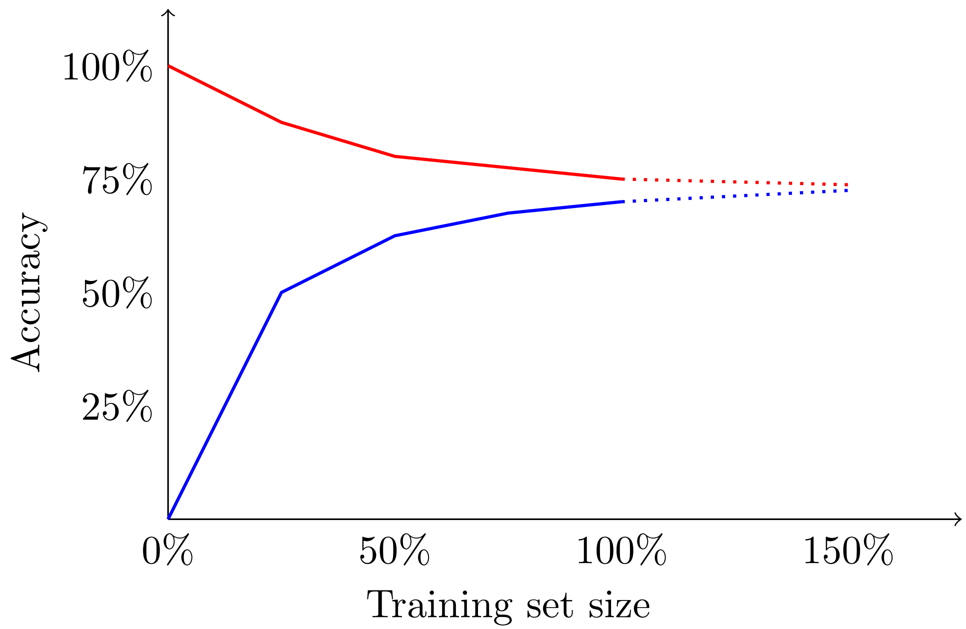
▷ Create dedicated test sets for each isolated problem.

Use external consistency checks to discover errors.

▷ Any test that works unlabelled data is good.

▷ Automatic checks for statistical anomalies.

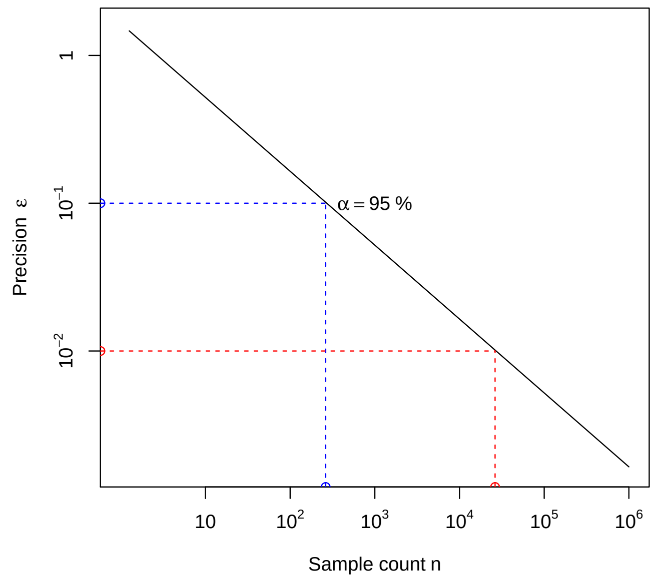
Diminishing returns



Most machine learning problems are not solvable by collection more samples.

▷ By reducing training set size it one can estimate potential gains.

Pitfalls of absolute performance measures



Test error estimates are not very precise:

- ▷ To increase precision 10 time you need 100 times more data.
- ▷ You can estimate test error with precision 1% not more.
- ▷ You cannot reliably detect progress on a reasonable test set.

Relative performance

Unlabelled data can be used for more precise performance estimates:

- ▷ Fix a good base line model.
- ▷ Evaluate both models on unlabelled data.
- ▷ Choose uniformly at random 100 - 1000 prediction differences.
- ▷ Establish the ground truth for these differences.
- ▷ Compute improvement ratio for differences.
- ▷ Compute relative frequency of difference.
- ▷ Their multiple is the relative performance gain.