

Applied clinical NLP: System Development Life Cycle

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VA Informatics and Computing Infrastructure

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Research areas in Clinical domains

- Clinical outcomes research
- Health services research
- Disease modeling
- Comparative effectiveness
- Prospective clinical studies

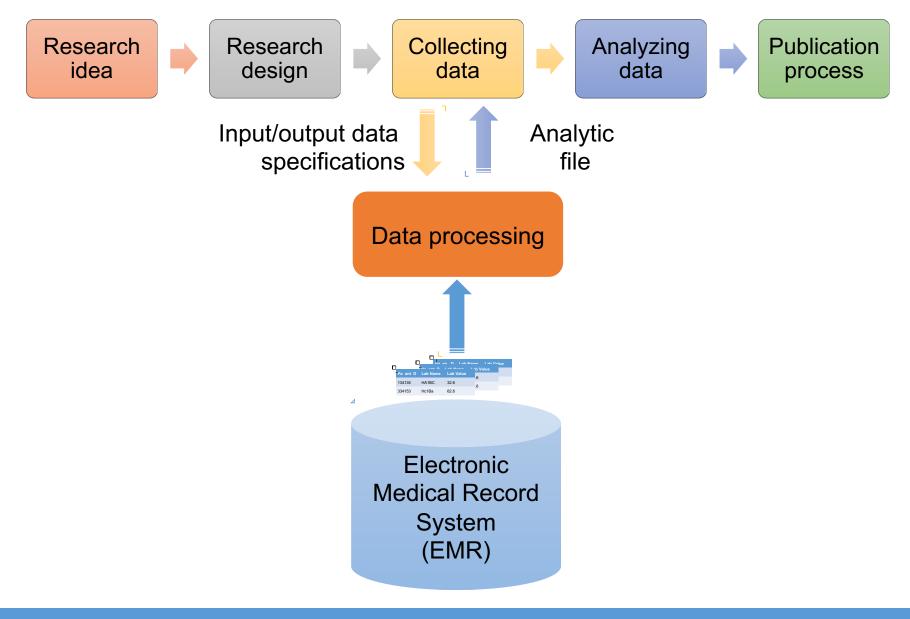


Secondary use of Electronic Medical Record

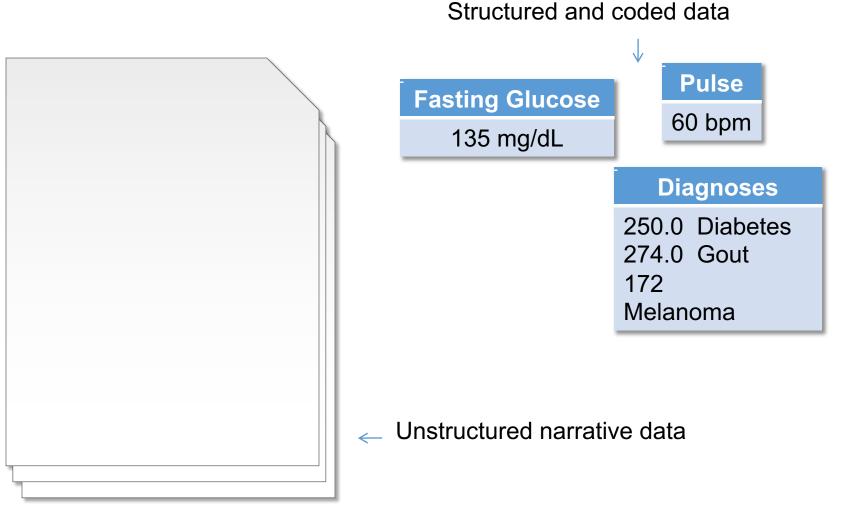
Cowie MR, Blomster JI, Curtis LH, et al (2017) Electronic health records to facilitate clinical research. Clin Res Cardiol 106:1–9.



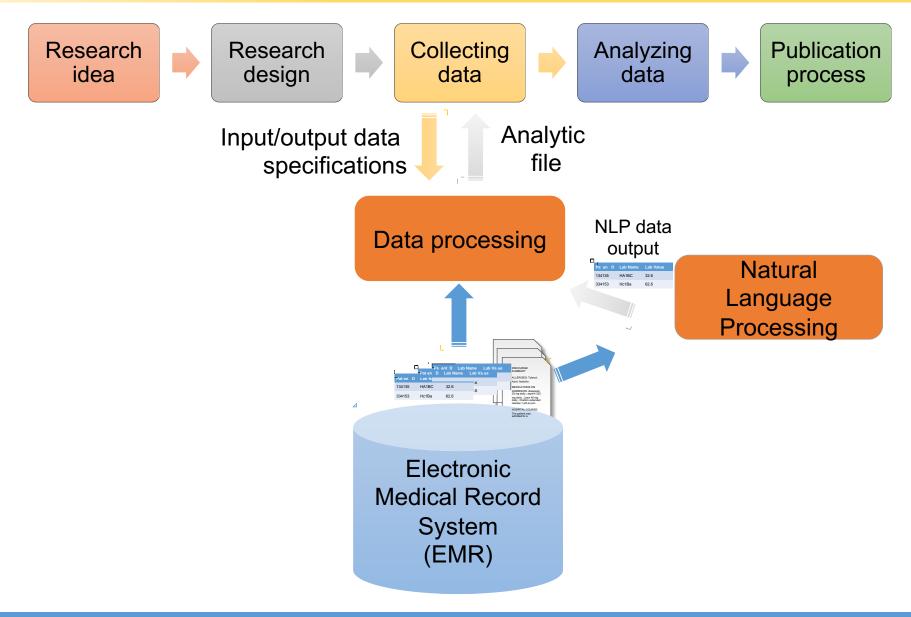
Clinical research project workflow



Data Types in the EMR

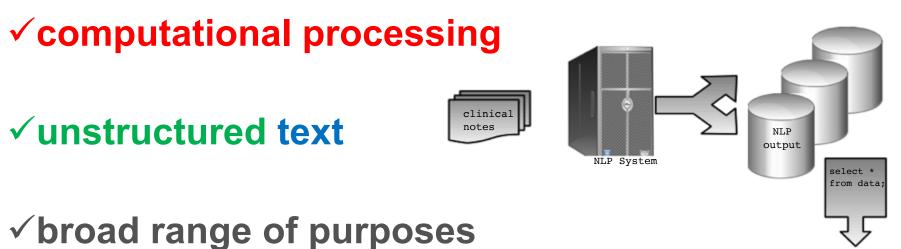


Clinical research project workflow



Natural language processing (NLP)

Natural language is automatically parsed into structured format

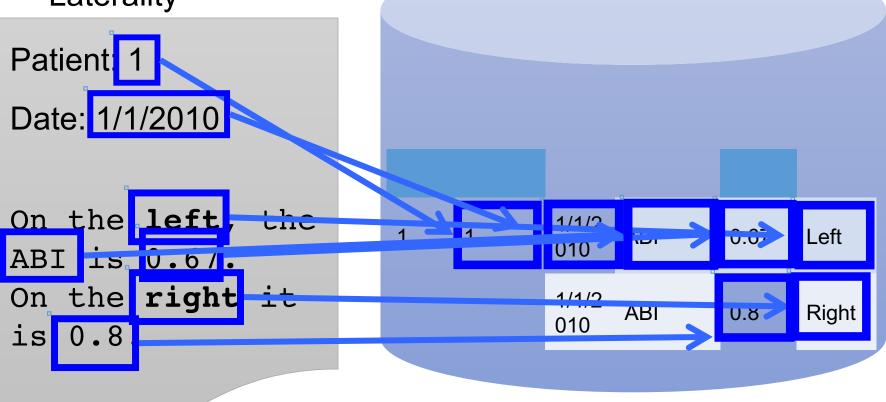


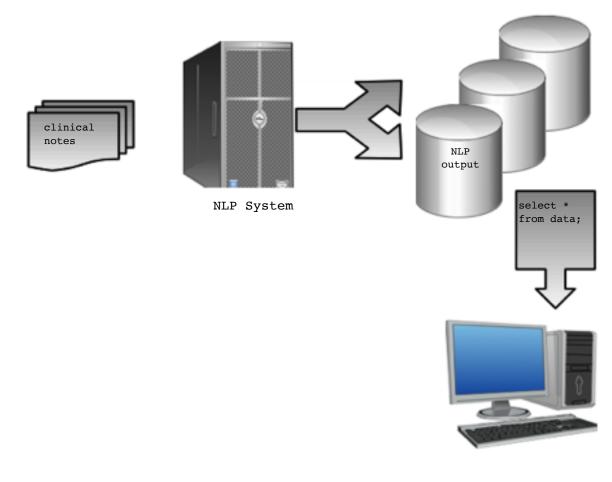


Information Extraction

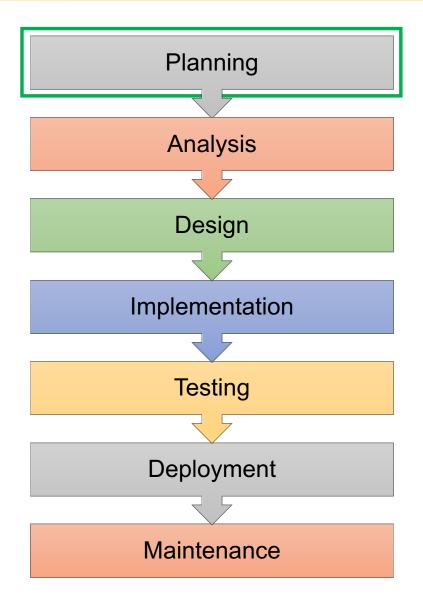
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- Ankle Brachial Index
 - Value
 - Laterality





System development life cycle





SDLC: Planning

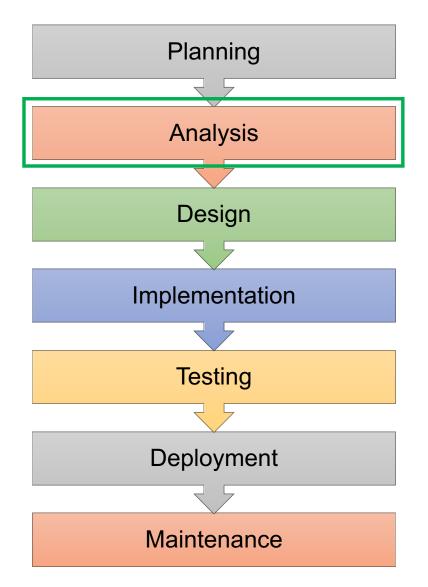
Adequately explicit concept definition

- "Concept = entity, idea, thought, meaning
- Clinical concept entity targeted by NLP
 - Examples:
 - Diagnosis, symptom, finding
 - Lab value
 - Vital sign measurements
- Characteristics of a clinical concept for NLP
 - single, unified meaning across all instances of the concept
 - · instances of the concept are directly comparable to each other
 - project specific definition
 - documented in electronic medical record (EMR)

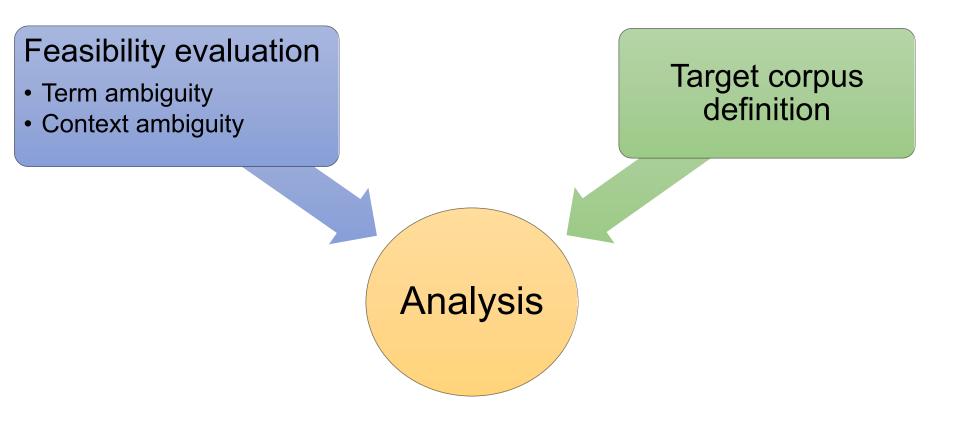
Concept sheets

- To **operationalize** your variables
- As a **communication** tool
- Elements
 - Concept name
 - Detailed definition
 - Attributes
 - Examples: What it is and what it is not

Concept: Ankle Brachial Index Definition: Explicit historical or current affirmed mentions of ABI numerical values, regardless of resting/after exercise, regardless of specific arteries Attributes: Laterality (left, right, bilateral, not specified) Exclude: pressure values









Feasibility analysis

- Estimate term ambiguity for concepts
 - Very ambiguous
 - abbreviation "PE"- Physical education, physical exam, pulmonary embolism, pulmonary edema, peak ejection, pleural effusion...
 - Not ambiguous
 - Fully spelled out phrase Left ventricular ejection fraction

Feasibility analysis

- Estimate <u>context ambiguity</u>
 - Common symptoms have ambiguous context
 - "patient denies fever"
 - "patient arrived at the ER with fever"
 - "patient takes care of her mother who has high fever"
 - "if fever occurs, call the nurse"
 - "if fever does not go down, take medication"
 - Rare diseases or conditions have less ambiguous context (unless they are side effects of a treatment)
 - "Genotype showed significant HIV drug resistance, including the following mutations in HIV reverse transcriptase: M41L, L210W, and T215Y"

The results of <u>feasibility analysis</u> may show that it is **not feasible** or it is **not practical** to develop a <u>fully automated</u> information extraction system and the project definition should change.

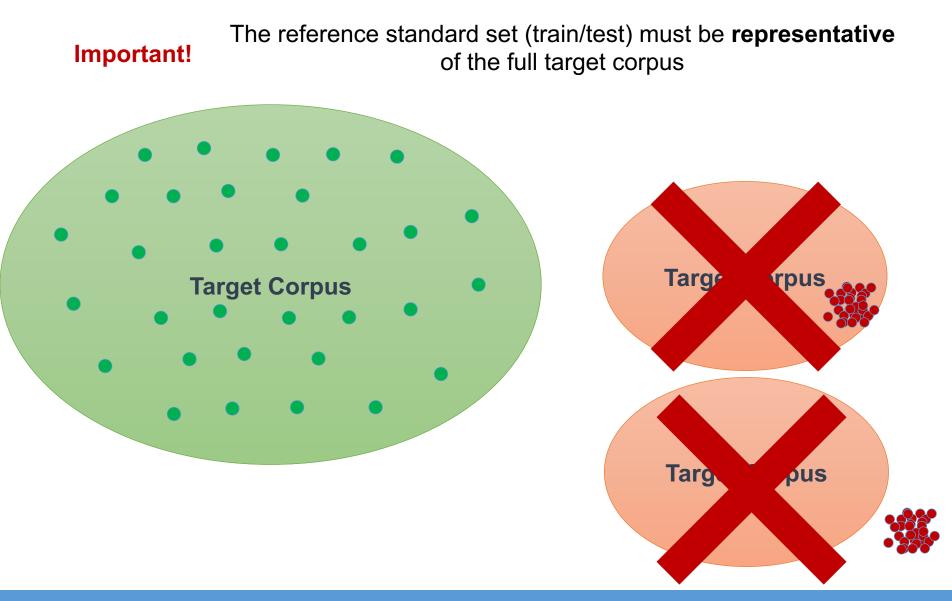
Alternative to fully automated information extraction is

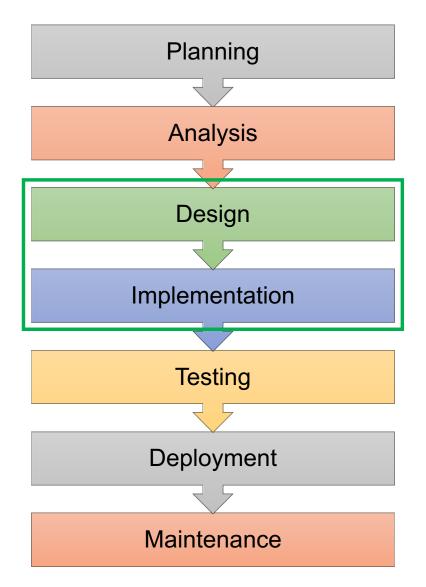
- NLP-assisted manual chart review
- Manual chart review
- Structured data analysis to utilize surrogates

Defining target corpus

Target corpus - the complete set of clinical notes that the NLP system will be designed to process

- Document selection for processing
 - Automatic information retrieval
 - Manual selection heuristics
- Document selection for manual annotation
 - Reference standard, training / testing set







SDLC: Design

Information model

 a representation of concepts, the relationships, rules, and analytic steps to achieve a specific goal

Full Language model (ex. English)

Sublanguage model (ex. Clinical)

Information model for NLP task (ex. concept-value extraction)

Knowledge base for a specific implementation on a specific corpus

Development of an information model

Text processing method	Information model component
Keyword search	Term list
Rules and patterns	Term lists Term sequence patterns Rule sets
Machine learning classification	Feature definitions Class list

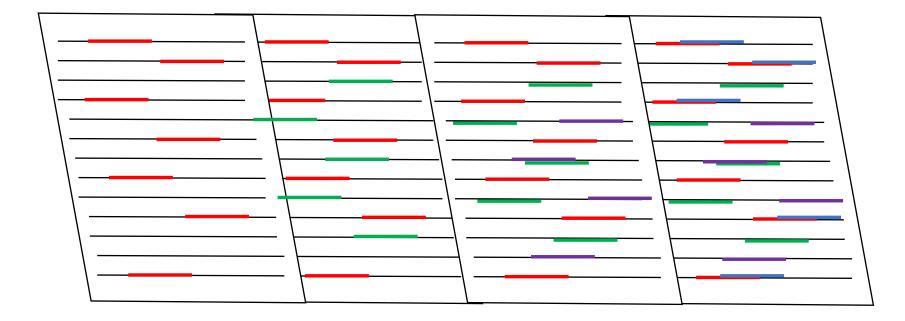
SDLC: Design

Approaches to knowledge base acquisition

- Knowledge-driven
 - Ontology, dictionary, terminology
- Expert-driven
 - Manually designed custom dictionaries, rules, heuristics
- Data-driven
 - Manually or statistically derived custom dictionaries, patterns, ML models
- Hybrid
 - · Combination of approaches, different for each step
- Ensemble systems
 - combine methods in parallel
 - select the best performing method using rules or statistics, or combine results from several methods (e.g., majority voting, weighted voting, machine learning classifier of outputs).
 - Ensemble systems have reliably demonstrated better performance than individual methods but are significantly more complex to implement.

Pipeline system implementation



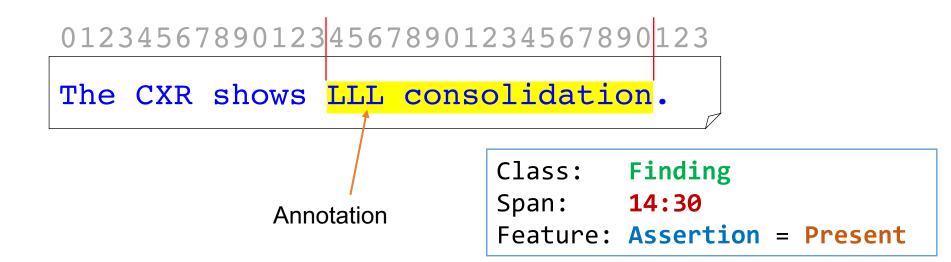


Pipeline annotations

Each module adds layers of annotations

<u>Annotation</u>

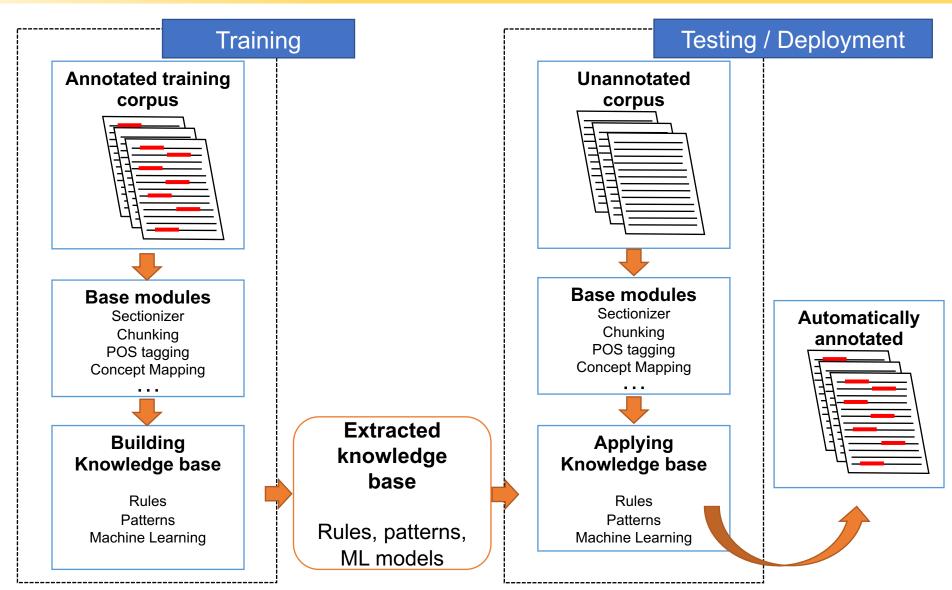
- Class assigned meaning to data
- Label = concept = annotation class = annotation type ≈ semantic type
- Span a pointer to start and stop points in a text
- Features attributes of the Class and their values
- Generated by human, machine, or human+machine.



SDLC: Implementation

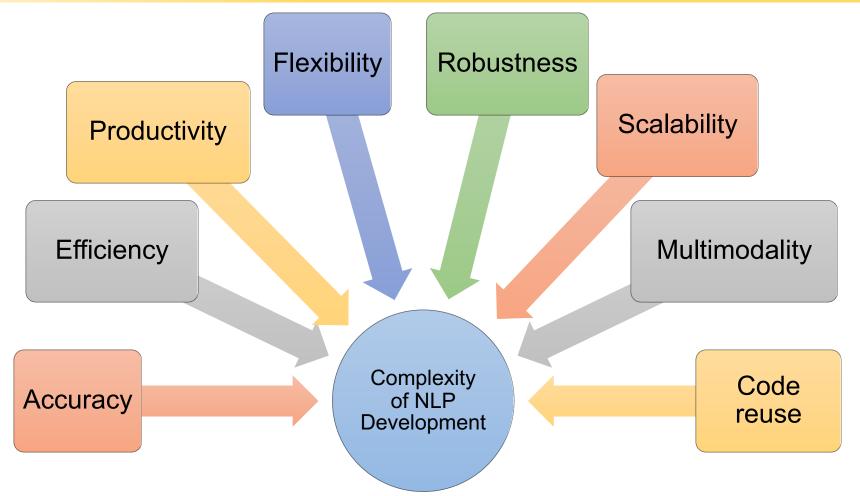
- An NLP pipeline with <u>data-driven knowledge base</u> has two versions:
 - one for training, and
 - one for testing (or deployment)

SDLC: Implementation



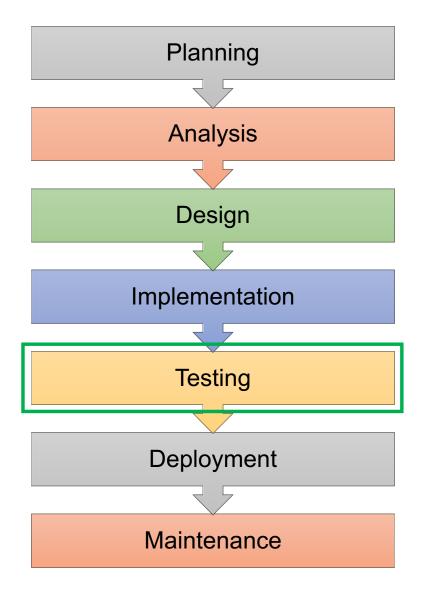
07/09/2020

SDLC: Implementation



Leidner JL. *Current issues in software engineering for Natural Language Processing*. HLT-NAACL 2003 workshop on Software engineering and architecture of language technology system. <u>http://portal.acm.org/citation.cfm?doid=1119226.1119233</u>

07/09/2020





SDLC: Testing

Validation

- Measures how <u>accurately</u> the NLP system performs extraction as compared to a *reference standard*
- Reference standard can be:
 - Manually annotated text
 - Benchmark system
- Measured in classic performance measures
 - Recall
 - Precision
 - F-measure

SDLC: Testing

Information extraction confusion matrix

	Reference standard		
	Annotation	No Annotation	
System annotation	True positive	False positive	Total system positive
No System annotation	False negative	True negative	Total system negative
	Total ref standard positive	Total ref standard negative	

 $Recall = \frac{True \ Positive}{Total \ Ref \ Standard \ Positive} = \frac{True \ Positive}{True \ Positive + FalseNegative} = Sensitivity$

$$Precision = \frac{True \ Positive}{Total \ System \ Positive} = \frac{True \ Positive}{True \ Positive + False \ Positive} = Positive Predictive Value$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

SDLC: Testing

Error analysis

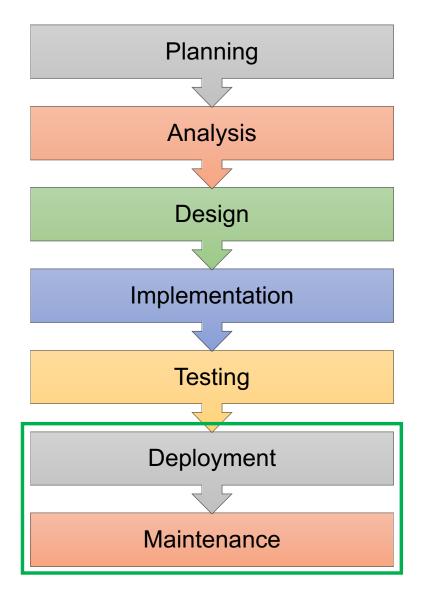
 manually examine the examples when system output did not match manual annotation and attempt to find the reason for the error

Systematic error

- The same reason for each instance of an error of that type
- Can be fixed by updating dictionary, or rules, or retraining machine learning step with a different feature set

<u>Random errors</u>

- New misspellings, new context
- Each error is different from other errors
- Cannot be fixed without significant decrease in recall or precision

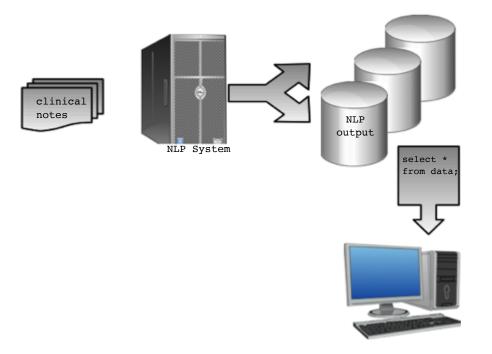




SDLC: Deployment

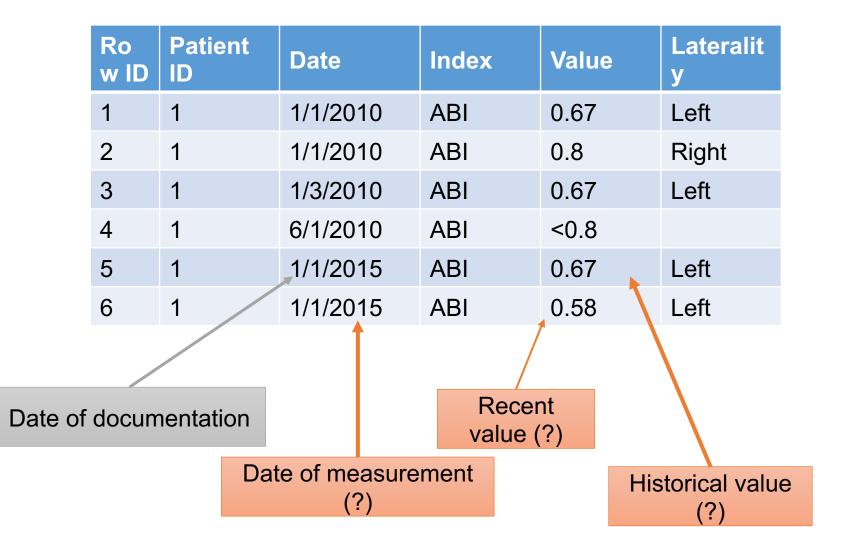
Deployment

- => NLP system is applied on the target corpus
- => output dataset is created



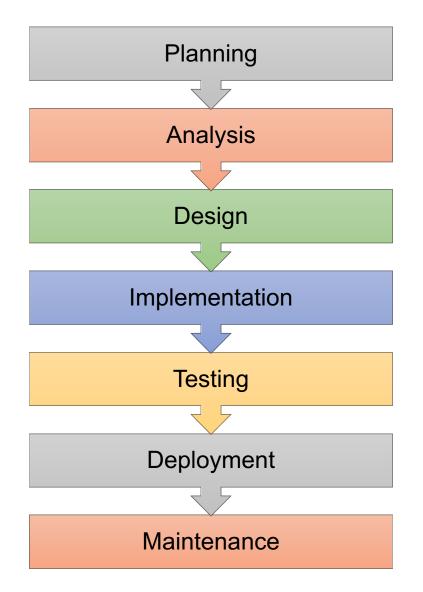


Applied NLP limitations

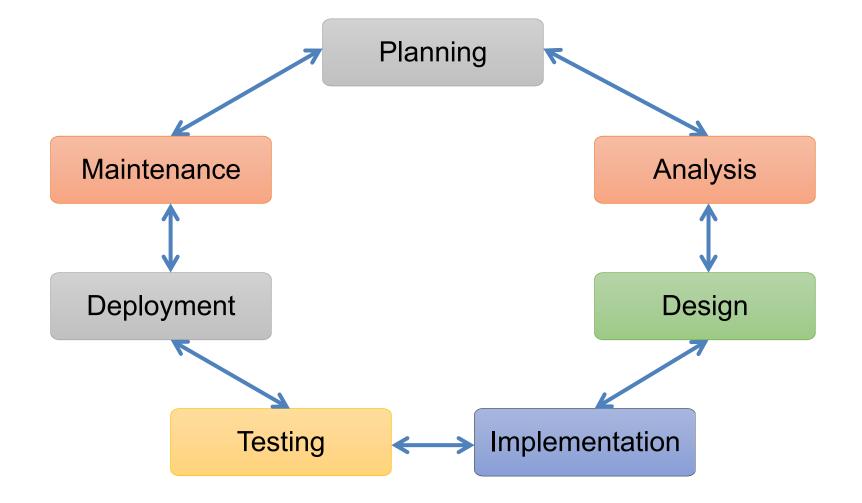


SDLC: Maintenance

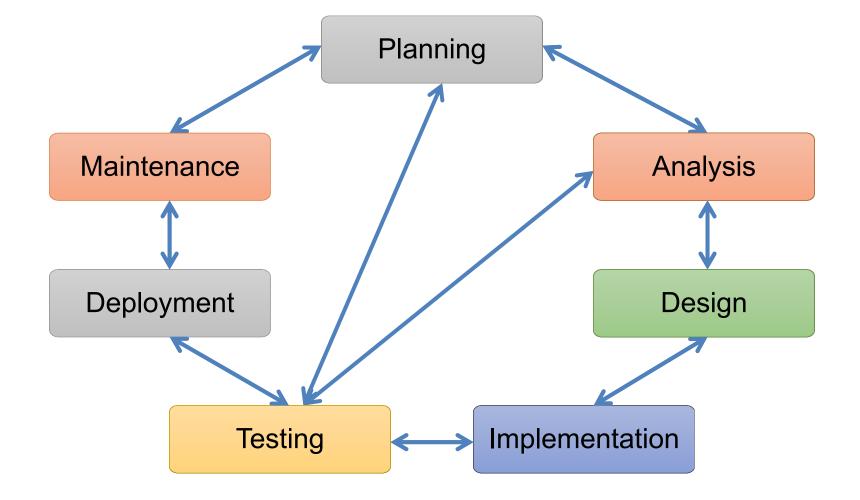
- Linguistic drift
 - Language changes over time
 - New words enter the lexicon (ebola, zika, covid)
 - Standard coding systems change (ICD9 -> ICD10)
- Settings change
 - New guidelines for documenting of care
 - Sublanguage variations across medical subdomains
- For systems that applied over time, regular validations are required
- Rules, patterns, ML models need to get updated



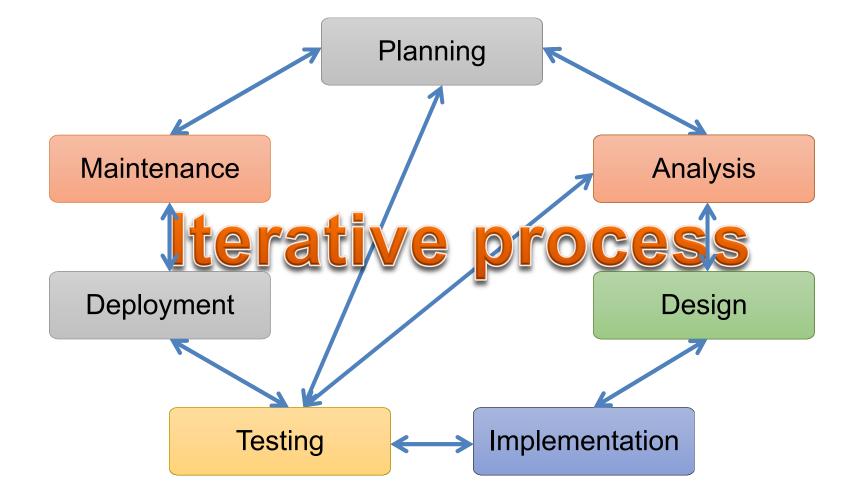














Contact Info

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