BUDDI Health

Deep Learning Platform

Medical Language Processor - “MLP® ”

May 2019

New York

Microsoft Partner

BUDDI MLP® (NLP) Technology Difference >

Structured Clinical Contextual Graph

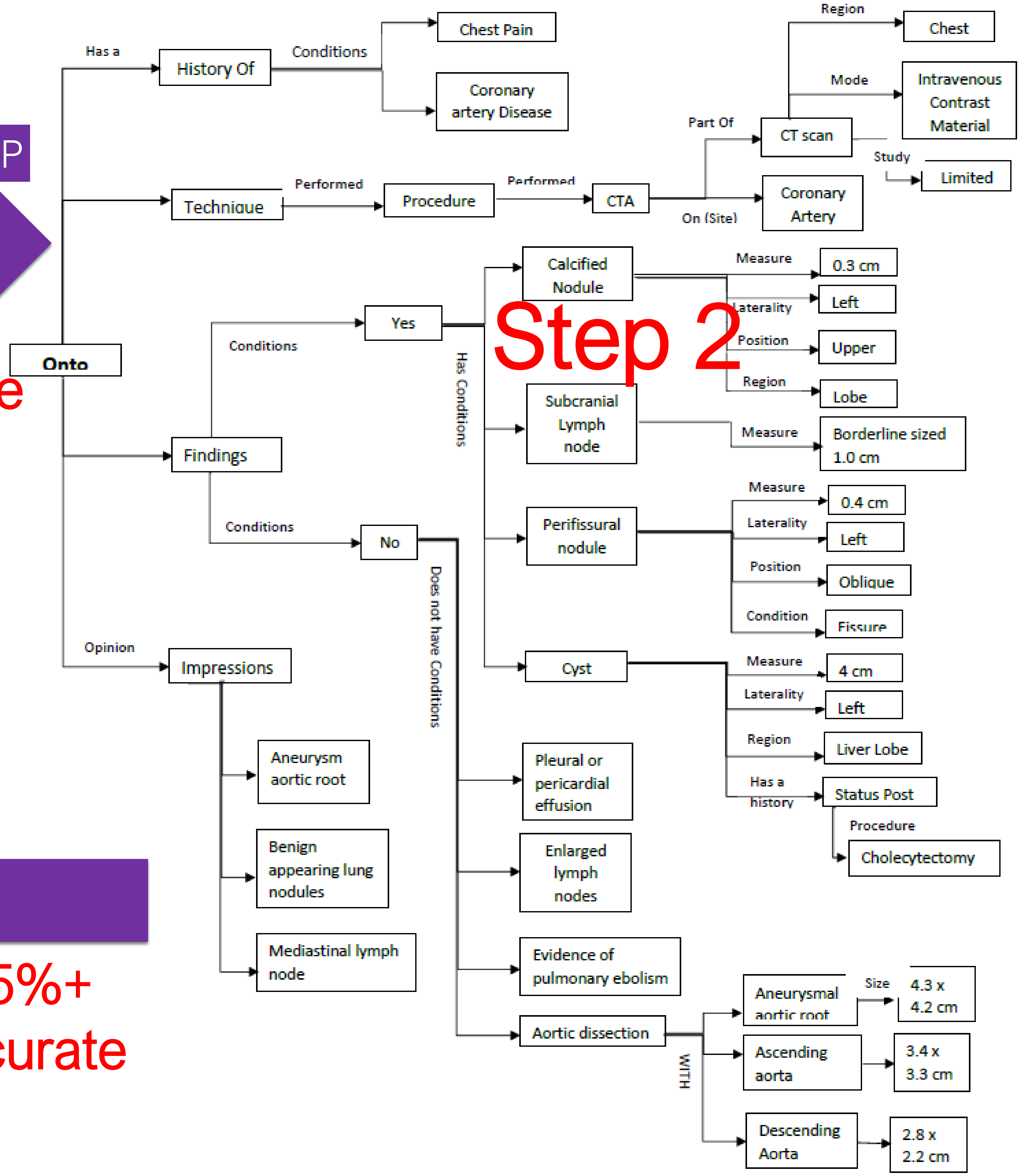
Un-Structured Medical Record from EPIC

post</history> <procedure>cholecystectomy</procedure> <bodypart>Bones</bodypart> unremarkable.IMPRESSION: 1. There is a <measurements>4.3 cm</measurements> <condition>aneurysm</condition> of the <region>aortic root</region>.2. There are two benign-appearing <bodypart>lung</bodypart> <condition>nodules</condition>.3. Borderline sized <region>mediastinal lymph node</region>, of uncertain significance.*** END OF ADDENDUM <date>05/01/2017</date> ***PROCEDURE DATE: <date>05/01/2017</date> Quantity of Contrast in Vial in ml: <measurements>100</measurements> Contrast Used: <contrast_material>Omnipaque 350</contrast_material>Quantity of Contrast Wasted in ml: <measurements>20</measurements>INTERPRETATION: I. Clinical Information: <age>52 years</age> <gender>Male</gender> with <laterality>right sided</laterality> <bodypart>chest</bodypart> <condition>pain</condition>II. Technique: <procedure>Coronary CTA</procedure> was performed on a <equipment_and_materials>256-slice cardiac CT scanner</equipment_and_materials> with <technique>prospective ECG gating technique</technique>. III. Procedure: <technique>ECG-gated CT</technique> <technique>without contrast material</technique> and <procedure>CT angiography</procedure> <technique>with contrast material</technique> of the <bodypart>heart</bodypart> and <region>coronary arteries</region>, including <procedure>3D image post processing</procedure> was performed.IV. Radiation Dose Exposure: DLP: <measurements>457.12 mGy.cm x 0.014</measurements> = Effective Dose <measurements>6.4 mSv</measurements>V. Study Image Quality: 3[1. The CCTA can be read using one best systolic or diastolic phase. 2. The CCTA requires adjacent systolic or diastolic phases. 3. The CCTA requires multiple phases from both systolic and diastolic phases. 4. [illegible] nondiagnostic study]VI: SL NTG: Yes yCardizem: No nMetoprolol: Yes Specify: <mode>Oral</mode> or [illegible] and total dose given <drug>metoprolol</drug> <measurements>50 mg</measurements> po x 1 doseHeart Rate: VII. Results A: Coronary Artery Calcium Score: Total Agatston Score: 45MESA Percentile Rank: 77 (The observed calcium score of 45 is at percentile 77 for subjects of the same age, gender, and race/ethnicity who are free of clinical cardiovascular disease and treated diabetes.)LM Agatston Score: 0LAD Agatston Score: 4LCX Agatston Score: 41RCA Agatston Score: 0B: Coronary Artery CT Angiogram Coronary Dominance: rightAnomalous coronary artery: No Coronary fistula: No Coronary arteries (segment number): LM (5): <medical_state>normal</medical_state>LAD: Prox (6) minimal <condition>calcific plaque</condition> <region>Mid</region> (7) <medical_state>normal</medical_state> <region>Distal</region> (8) <medical_state>normal</medical_state> D1 (9) <medical_state>normal</medical_state> D2 (10) naLCX: Prox (11) <severity>mild</severity> <condition>calcific plaque</condition> OM1 (12) <medical_state>normal</medical_state> <region>Mid</region> (13) <medical_state>normal</medical_state> OM2 (14) <severity>mild</severity> <condition>calcific plaque</condition> LPDA (15) na RI (17) na LPL (18) naRCA: Prox (1) <medical_state>normal</medical_state> <region>Mid</region> (2) <medical_state>normal</medical_state> <region>Distal</region> (3) <medical_state>normal</medical_state> RPDA (4) <medical_state>normal</medical_state> RPL (16) <medical_state>normal</medical_state>{% diameter stenosis: <medical_state>Normal</medical_state> <measurements>0%</measurements>; Minimal <measurements>1 to 25%</measurements>; <severity>Mild</severity> <measurements>26 to 50%</measurements>; <severity>Moderate</severity> <measurements>51 to 75%</measurements><severity>Severe</severity> <measurements>76 to 99%</measurements>; T.O. <measurements>100%</measurements>}

Step 1

BUDDI MLP

95%+ accurate



Step 2

95%+ accurate

Step 3

BUDDI Real Time CDI.Ai
BUDDI Real Time CODING.Ai

PROVIDER - Ai Enabled Applications

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#1

Components Inside BUDDI's NLP >

Sentence Boundary Detection

Identifying the correct boundary of a sentence. Sentence boundary detector identifies that the boundary of the sentence that it does not end at b.i.d. but at "frequently".

e.g. The patient takes aspirin 325 mg b.i.d. frequently since May.

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#2

Components Inside BUDDI's NLP >

Section Detection

Unstructured clinical data primarily consists of healthcare documents transcribed based on physician dictations where the physician dictates the entire encounter he had with a patient.
There could be different elements of this document which are classified into various sections like History of Present Illness, Past Medical History, Past Surgical History, Current Medications, Allergies, Physical Examination, etc.
These sections may be documented in different forms in different hospitals and different physicians.

e.g. History of Present Illness may be documented as HPI, Present Illness, Brief History etc.

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#3

Components Inside BUDDI's NLP >

Tokenizer

This component breaks down a sentence into its constituent tokens so that the next component which is the Part of Speech tagger can assign a POS tag to each constituent token.

e.g. The tokens are generated as

Word Token 1: The
Word Token 2: patient
Word Token 3: takes
Word Token 4: aspirin
Number Token 1: 325
Word Token 5: mg
Word Token 6: b.i.d.
Word Token 7: frequently
Word Token 8: since
Word Token 8: May
Symbol Token 1: .

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Components Inside BUDDI’s NLP >

Part of Speech (POS) Tagger

POS tagger tags the different grammatical components of a sentence based on Part of Speech like Noun, Verb, Adjective etc.

e.g. The patient takes aspirin 325 mg b.i.d since May.

The/DT
takes/VBZ (Verb)
325/CD (Cardinal Number)
b.i.d/NN (Noun)
May/NN (Noun)

patient/NN (Noun)
aspirin/NN (Noun)
mg/NN (Noun)
since/IN (Preposition)
./.

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Components Inside BUDDI's NLP >

Chunker

Chunker breaks a sentence into different phrases like Noun Phrases (NP), Verb phrases (VP), prepositional phrases (PP) Adjective Phrases (ADJP) etc. as per syntactic rules.

e.g. "Sensation is intact to light touch in both lower extremities" is broken down.

The chunker output would be:
Sensation (NP) > is (VP) > intact (ADJP) > to (PP) > light touch (NP) > in (PP) > both lower extremities (NP)

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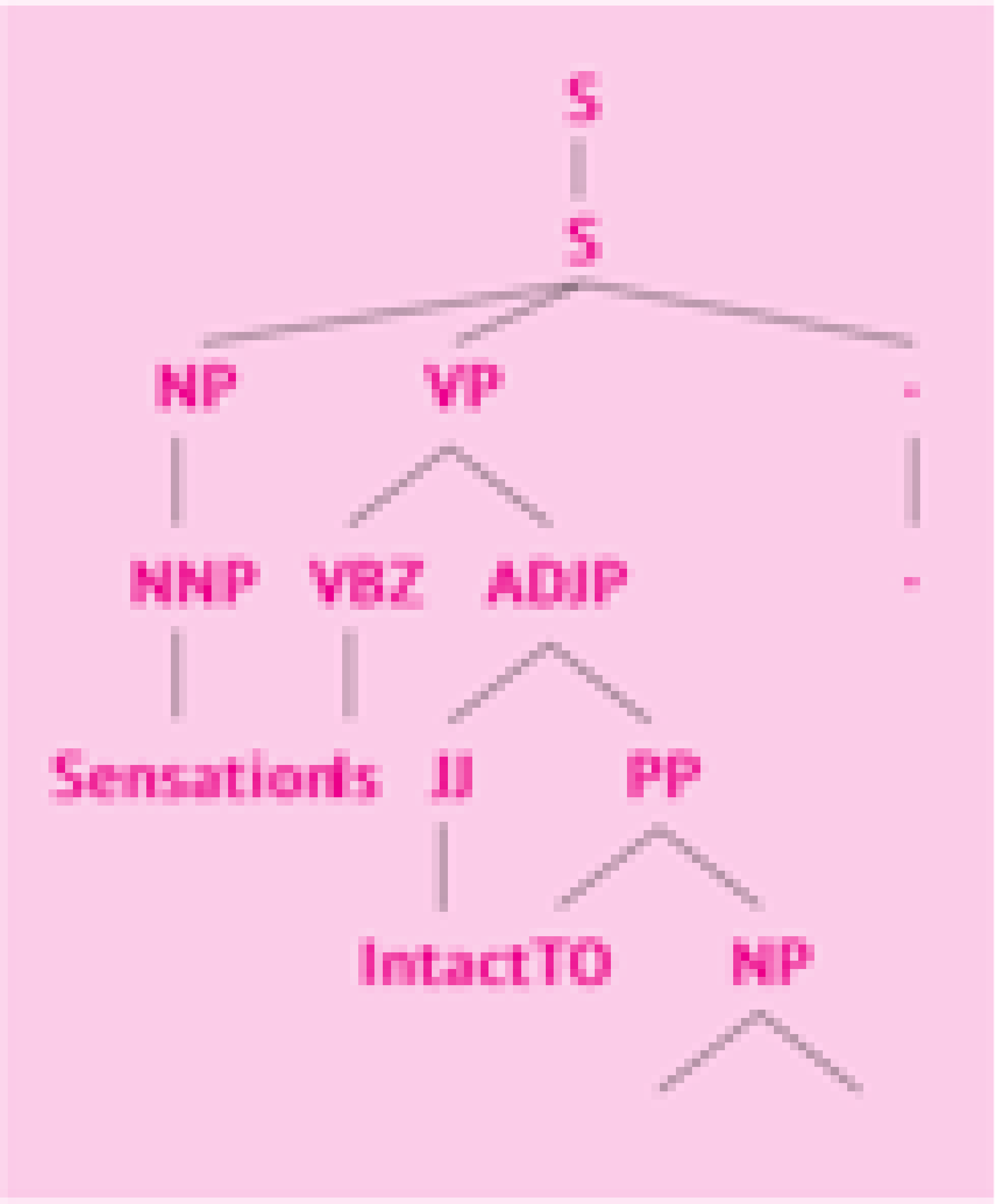

Parser

Parser establishes relationships between different phrases in a sentence following phrase structure rules as defined in syntactic English grammar.

e.g. "Sensation is intact to light touch in both lower extremities"
The parser gives the output as show in the visual.

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Component

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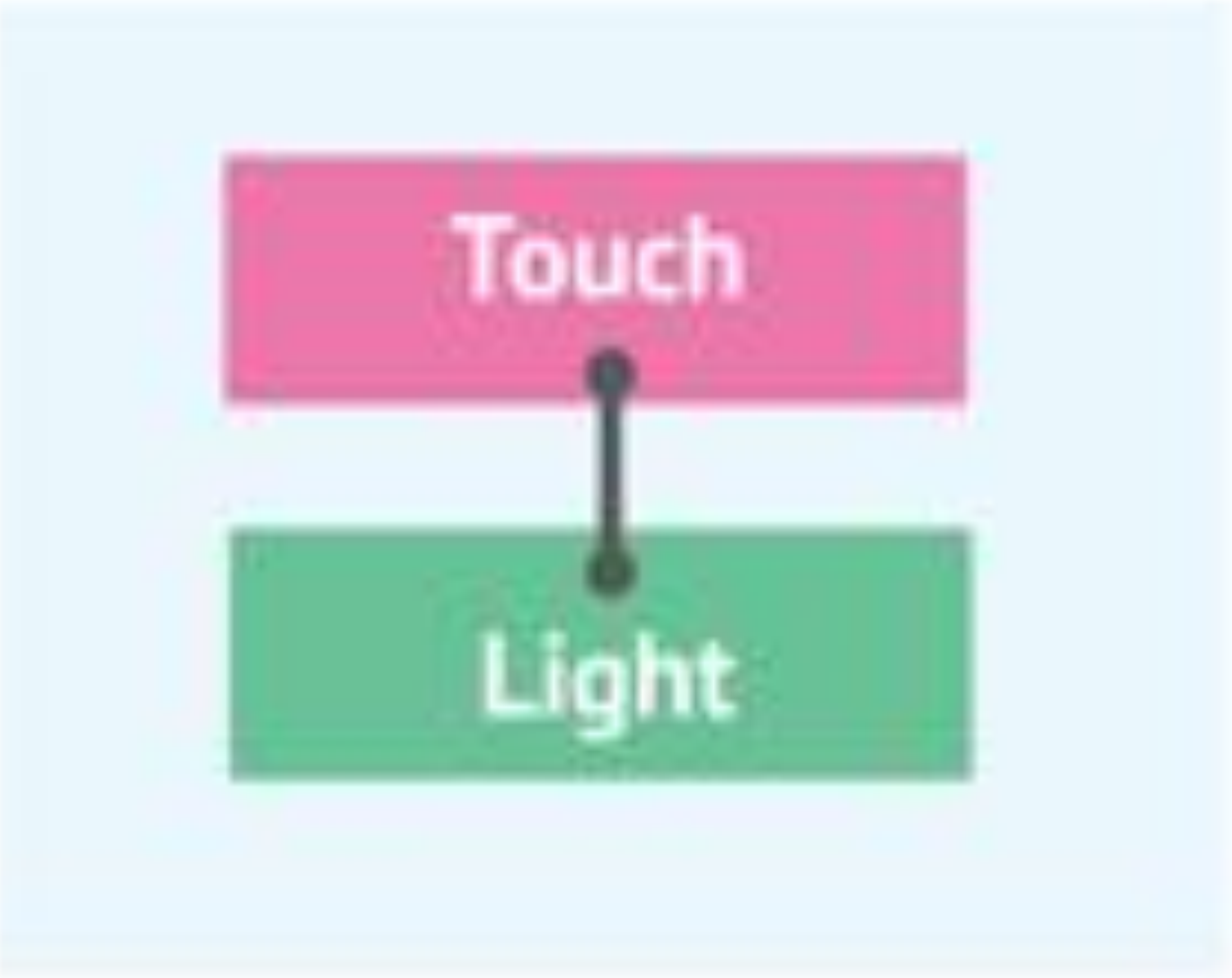

Dependency Parsing

This component establishes relationship between different words in a sentence.

e.g. "Sensation is intact to light touch in both lower extremities"
As shown in the visual, the dependency parser relates intact<--> sensation, touch<--> light and so on

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Dictionary Lookup Process

The dictionary look up component of NLP maps the concepts identified from the document against concepts present in the ontology which is a comprehensive collection of medical concepts classified into their types. Based on this look up, it assigns tags of disease (problem), procedure, anatomical structure etc. to the concepts.

e.g. "The patient takes metformin for his diabetes" Metformin is tagged as a medicine and diabetes as a disease or problem.

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Relationship Finder

NLP has a built-in algorithm that establishes the primary level of relationship between concepts such as anatomical structure and problems or diseases, procedures and anatomical structure and procedure and medical devices.

e.g. "The patient has intermittent pain located on the left side of his chest."
NLP can relate pain to the chest and identifies chest pain although they are not co-located within the sentence.

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UEI Detection

The UEI (Unique Entity Identifier) detection module uses the relationships identified between different words in a sentence to identify matching concepts in the ontology or knowledge base to assign a unique identifier called a UEI or Unique Entity Identifier.

e.g. "The patient complains of pain in the leg"
The ontology has a UEI for leg pain. The UEI detection module identifies that "pain in the leg" is the same as "leg pain" and assigns it the relevant UEI.

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Negation

NLP has a negation-detection algorithm that identifies such indicators to identify negation in sentences.

e.g. "There is absence of any cardiac enlargement"
Here the word "absence" indicates that cardiac enlargement is not present or is negated.

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Components Ins

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Temporal Section Detection

Temporal Status Detection is a component of NLP that identifies the status of each concept with respect to its temporality which is present, past, future etc.

e.g. "The patient has had an MI in the past"
The sentence is the past tense, detected by the word 'past' and its mapping with 'MI'.

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Modifier Detection

Modifiers are terms used to further describe the specificity of concepts in a medical document. This component identifies which concept with a modifier is related to and forms the groups of words like â€˜intermittent painâ€™ are marked as modifiers for pain.

e.g. "The patient has intermittent pain located on the left side of his chest"
'Intermittent' and 'Pain' words are grouped to specify the concept.

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Components Inside BUDDI's NLP >

Drug Mention Annotator

There are various attributes associated with a drug (medicine). The drug mention annotator identifies the various parameters and establishes a relationship between the drug and its parameters.

e.g. "The patient's Lasix was changed from 20 mg to 40 mg tablets p.o. b.i.d."

Drug: Lasix

Strength 20 mg, 40 mg

Route: p.o. (by mouth)

Frequency: b.i.d (twice a day)

Status: Change.

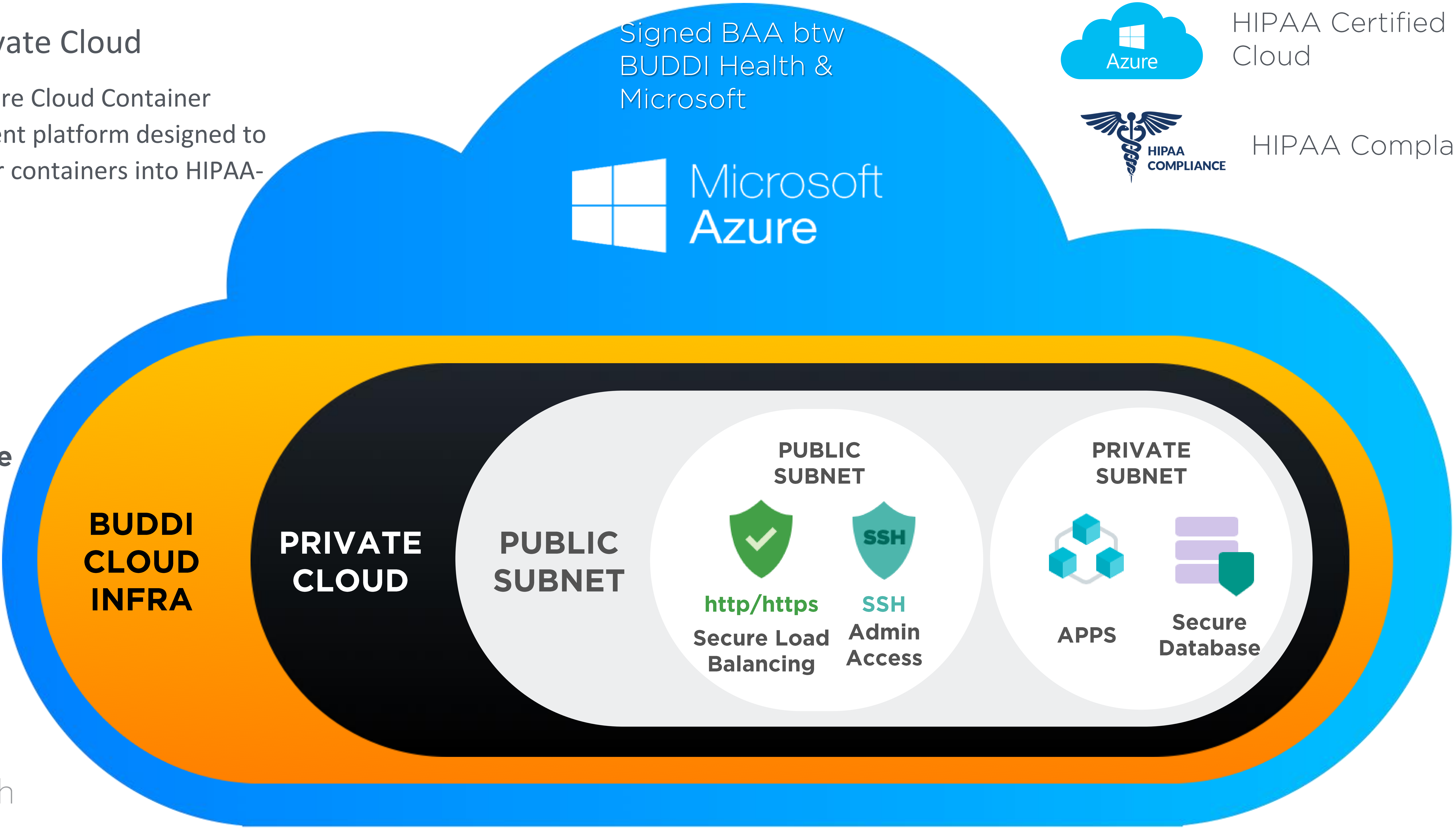
BUDDI hosted on HIPAA Certified Cloud

HIPAA Secure Private Cloud

The BUDDI HIPAA Secure Cloud Container Platform is a deployment platform designed to securely deploy Docker containers into HIPAA-ready environments.

HIPAA Certified Cloud

HIPAA Complaint



We manage zero-downtime deployments, scale your clusters, encrypt and run your ops seamlessly.

Contact Us

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