NATURAL LANGUAGE PROCESSING

ENABLING THE POTENTIAL OF A DIGITAL HEALTHCARE ERA

CHILMARK RESEARCH

MARKET SCAN REPORT

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Executive Summary

The great struggle to digitize the business of healthcare and practice of medicine is over; however, the war to wrangle and analyze the data collected will rage on for years. In the rush to digitize and not unreasonably disrupt established clinical workflows and documentation practices, as much as 80 percent of the data captured by IT systems is unstructured, and the text is often poor quality. In its current format and given the high cost in human time and effort it would take to read, the extensive library of health data is effectively unusable. Thus, the quest to drive better healthcare decision making and analytics remains an unfulfilled promise.

Yet the need to leverage unstructured data is growing in importance as the business model for reimbursement of care shifts from fee-for-service to value-based care (VBC). Natural Language Processing (NLP), a subcategory of artificial intelligence (AI), has the ability to augment and automate human behaviors and skills. It can be used to parse and abstract key information from a variety of sources, such as clinician notes, thereby unlocking unstructured data and helping ease payers and providers through the transition to a new reimbursement model. This augmentation - leading to automation of such mundane tasks as quality reporting and creating patient registries among others - has the potential to save healthcare organizations (HCOs) significant money and time.

The current market for NLP technology in healthcare is nascent, dominated by a few legacy vendors that are focusing on front-end speech recognition (for computer assisted physician documentation) and back-end coding (to optimize billing). While a number of tech giants continue to advance NLP technology for more general use, there are only a handful of niche solutions from highly specialized healthcare vendors pursuing additional use cases. We have outlined several of these vendors in this report. Many academic institutions are also developing their own solutions, often using open-source software. Such academic solutions offer the potential that joint ventures with vendors could lead to commercialization and potentially broader acceptance of NLP.

The best-performing NLP engines are able to combine the precision of traditional rule-based methods with advanced machine learning methods. State-of-the-art NLP systems also exploit the latest in deep learning methods – they excel by utilizing painstakingly developed gold-standard (i.e., expert-annotated) training datasets to learn how to classify new cases based on the accumulated knowledge of all historical cases.

This report describes a dozen significant NLP healthcare use cases, including computer assisted coding, speech recognition, and data mining. Five of these solutions have proven ROI and are commercially available from numerous well-established vendors. Another four are going through the initial phase of the adoption cycle and are primed to have an immediate impact under the new value-based care paradigm. These solutions focus on identifying the highest-cost patients earlier, tracking basic quality metrics related to annual follow-up, and reducing readmissions. The last group of solutions will mature over the next three-plus years and includes computational phenotyping for precision medicine, ambient virtual scribes to improve the electronic health record (EHR) user experience, and digital biomarker discovery using advanced voice-based diagnostic techniques.

There are many challenges to developing sophisticated NLP applications; these include the complexity of natural language, multiple technology approaches, and choice of metrics to measure success. Implementing NLP brings yet more challenges, including hiring people with specialized skills and achieving data liquidity. While these challenges are not insurmountable, they require a full appreciation of what it will take to succeed.

This report provides insights and advice for HCOs that are considering, implementing, and deploying NLP technologies. Following months of market research and interviews with healthcare providers and NLP vendors, we have compiled advice regarding newer technologies, proven methods, and the most impactful use cases. We also identify and analyse key performance metrics that users should expect to see cited by NLP vendors as key differentiators. This report concludes with profiles and analysis of a dozen significant NLP-focused vendors that Chilmark Research considers representative of the stack of technologies, development platforms, use cases, and services.

Market Dynamics

Natural Language Processing (NLP) is a subfield of computer science, computational linguistics, artificial intelligence (AI) and machine learning (ML). It has several sub-disciplines, including Natural Language Understanding (NLU), Natural Language Generation (NLG), and Natural Language Query (NLQ). NLP can be defined as the automatic processing of human natural language.

NLP has two large, overarching and related use cases:

1. Understanding human speech and extracting meaning.
2. Unlocking unstructured data in documents and databases by abstracting out key concepts and values and making this information available for decision support and analytics.

Nearly everyone uses NLP technologies every day without even realizing it. Spellcheck is the original NLP feature and one of its most common use cases. Voice assistants such as Apple's Siri are routinely used to improve a user's smartphone experience. Search engine use of NLP is also commonplace. In 2016, Google changed the algorithm powering its search engine from its original keyword-driven algorithm to a natural language query approach. Google Translate also uses NLP for machine translation to present any webpage in the native language of the browser.

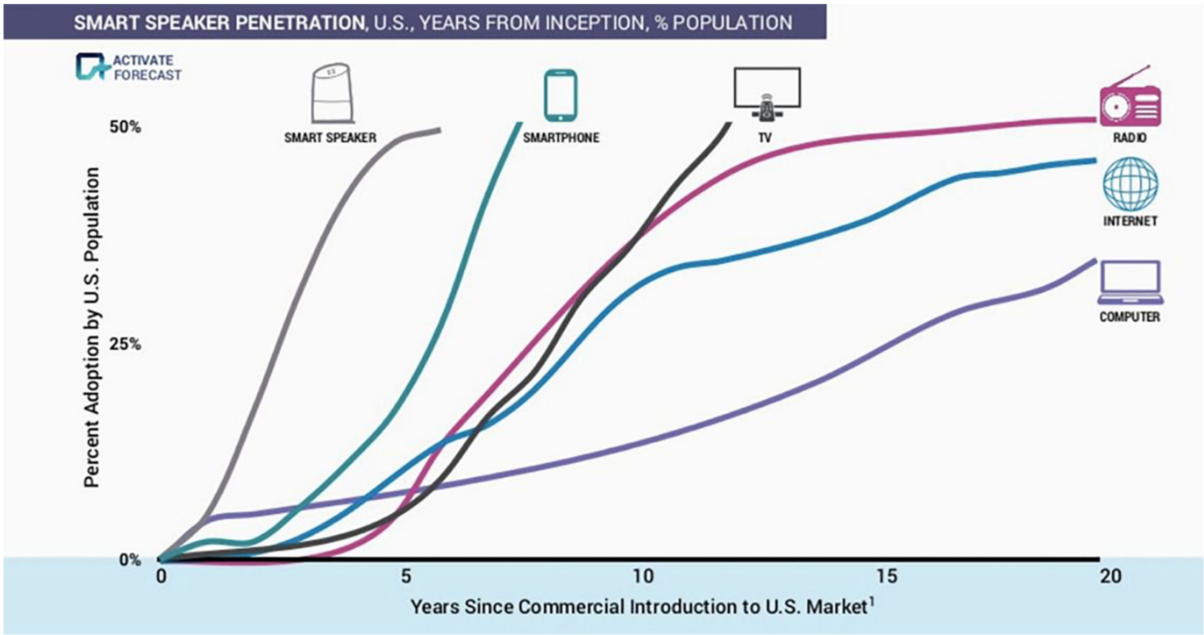

Figure 1: Ambient Virtual Assistant adoption rate relative to previous consumer technology paradigms

The most significant advancement in consumer adoption of NLP is the rapid adoption of ambient voice assistants built into smart speakers. Consumers have already filled their homes and lives with this newest category of consumer device faster than any other in history – a few years rather than a few decades. (See Figure 1.) Since the beginning of 2017, 400 million Android users were introduced to Google Assistant. Amazon's Alexa, with 39 million such devices sold in the US as of the end of 2017[1], is on track to reach 55-percent of households by 2022.[2] Since 2017, the number of Alexa Skills went from 7,000 to 40,000.[3]

We project Alexa's Skills to start growing exponentially as Amazon continues offering tools that make it easier for non-technical users to create their own customized skills. (See Figure 2.)

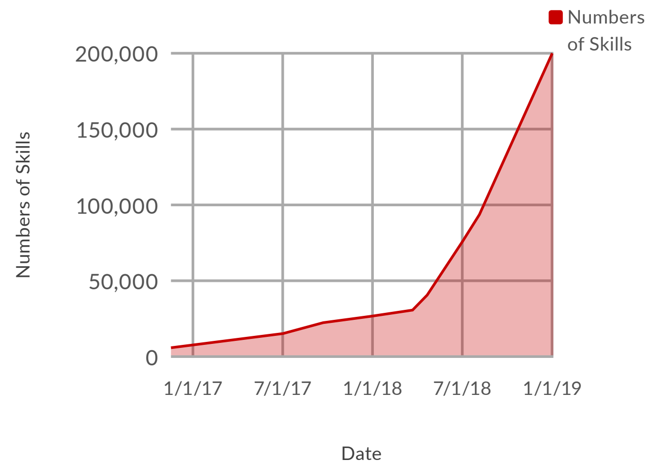

Figure 2: Projected growth in Alexa Skills

DRIVERS FOR NLP IN HEALTHCARE

The long-promised digitization of the business of healthcare and practice of medicine is nearly complete. This major accomplishment in the quest to modernize the industry has given rise to a population-scale dataset with unprecedented potential to generate insights that provide opportunities to improve quality of care and decrease costs. The next stage of this digitization journey will require advances in the two key areas of NLP, speech interfaces and analyzing unstructured data.

Three main imperatives are driving the need for healthcare-specific NLP:

1. Supporting the needs of value-based care (VBC) and population health management (PHM).
2. Coding and analyzing encounters more effectively.
3. Decreasing physician workload and burnout.

Support for VBC and PHM. The shift in business models and outcomes is driving the need for better use of unstructured data. Legacy health information systems have focused almost exclusively on extracting value from the 20 percent of clinical data that is captured in structured, computable formats. Next-generation management care and PHM applications, patient engagement portals, and advanced predictive/prescriptive analytics algorithms will be limited in their impact unless they can also tap into the information locked up in the 80 percent of clinical data that is unstructured. NLP offers a viable technical solution to this problem.

Coding. Because payers could arbitrarily approve or deny claims without auditing the EHR, this has led to widespread deficiencies in clinical documentation practices. Clinical documentation was traditionally used to inform billing/coding teams who would in turn use their specialized knowledge to choose the code with the highest reimbursement rate. With the shift from patient-level to population-level metrics for determining reimbursement demands, coders have had to shift their workflow from accurately documenting procedures and therapies to accurately documenting all diagnoses and related complications/comorbidities.

Physician Workload and Burnout. One of the greatest complaints of physicians today is the soul-crushing user experience of current-generation EHRs. Research has determined that for every hour spent in direct contact with patients, physicians now spend two hours doing EHR-based clerical work. As a direct result, physician burn-

Appendix A: Scope and Methodology

For this report, Chilmark Research identified more than 250 vendors that claimed NLP capabilities in healthcare. From this long list, Chilmark combined secondary and primary research methodologies to identify more than two dozen healthcare NLP companies that had a level of "market mind-share." These meetings and calls were typically 30 to 60 minutes including discussions of market drivers, technology, use cases, clients, adoption, pricing, and competition.

Chilmark also had discussions with many academic medical centers, consultants, and some government entities involved in reporting registries and NLP research. These interviews provided further perspectives on NLP, core use cases, vendors of note, and specific vendor experiences.

From this work, a subset of a dozen NLP companies were chosen based on multiple factors, including their experience/traction in healthcare, the breadth (or uniqueness) of their solution, their technology approach, and their results. Vendors all had an opportunity to review their profile and provide comments, which were considered and, where relevant, incorporated into the profile. In the end, the final vendor assessments are from the Chilmark Research analysts who authored this report. Only one vendor (Optum) opted to not provide feedback/review of their profile.

In compiling this extensive report, Chilmark Research maintained absolute objectivity throughout the entire research process, and it is our sincere hope that this report brings greater clarity to this rapidly developing and potentially high-value market.

Appendix B: Measuring NLP Performance

Developing useful and powerful NLP applications is all about optimizing methods to improve performance using annotated training datasets. The performance of NLP systems can be crucial in determining whether to apply those systems alongside humans or replace humans and calculating ROI. The two most important measures are precision and recall. The F1 score is calculated by averaging the precision and recall and represents the . The goal of any NLP system is to achieve optimal performance on both measures. (See Table 7.)

		Actual	
		Positive	**Negative**
Predicted	**Positive**	TRUE POSITIVE	FALSE POSITIVE
	Negative	FALSE NEGATIVE	TRUE NEGATIVE

Table 7: The Confusion Matrix: A Standard Method of Visualizing NLP Performance

Examples of metrics for different types of NLP processing include the following:

Auto Summarization

When comparing auto-summarization applications to human performance, BLEU and ROUGE scores are variations of precision and recall respectively.

- BLEU scores measure how often the words that appeared in the machine-generated summary appeared in the human-reference summaries.[111]
- ROUGE scores measure how often the words that appeared in the human-reference summaries appeared in the machine-generated summary.

Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar et al. '16)	82.304	91.221
1 Jan 22, 2018	Hybrid AoA Reader (ensemble) *Joint Laboratory of HIT and iFLYTEK Research*	82.482	89.281
1 Mar 06, 2018	QANet (ensemble) *Google Brain CMU*	82.744	89.045
1 Feb 19, 2018	Reinforced Mnemonic Reader + A2D (ensemble model) *Microsoft Research Asia & NUDT*	82.849	88.764
2 Jan 5, 2018	SLQA+ (ensemble) *ALibaba iDST NLP*	82.440	82.607

Figure 11: Algorithms That Outperform Humans at Reading

Automatic Speech Recognition

When assessing automatic speech recognition (ASR) systems, Word Error Rate (WER) is the standard measure. To determine WER, the ASR output is dynamically aligned to a reference transcript, which then identifies three different types of error: Substitution errors, insertion and deletion errors.

Reading Comprehension

Stanford Question Answering Dataset (SQuAD) is a test of reading comprehension based on a dataset of more than 500 Wikipedia articles and 500,000 question-answer pairs associated with the articles.[112] At the end of 2017, humans remained unequaled in their question answering skills, but in the five months since the start of 2018 at least four separate research groups from Microsoft, Alibaba, Google, and China's Joint Laboratory of HIT and iFLYTEK Research have bested humans on the SQuAD dataset.[113]

Transcribing Conversations

Algorithms have also now matched humans at transcribing conversations, achieving 95-percent Word Accuracy (WAcc) using the Switchboard HUB5'00 data set of 40 audio files and the corresponding human transcriptions.[114] (See Figure 12.)

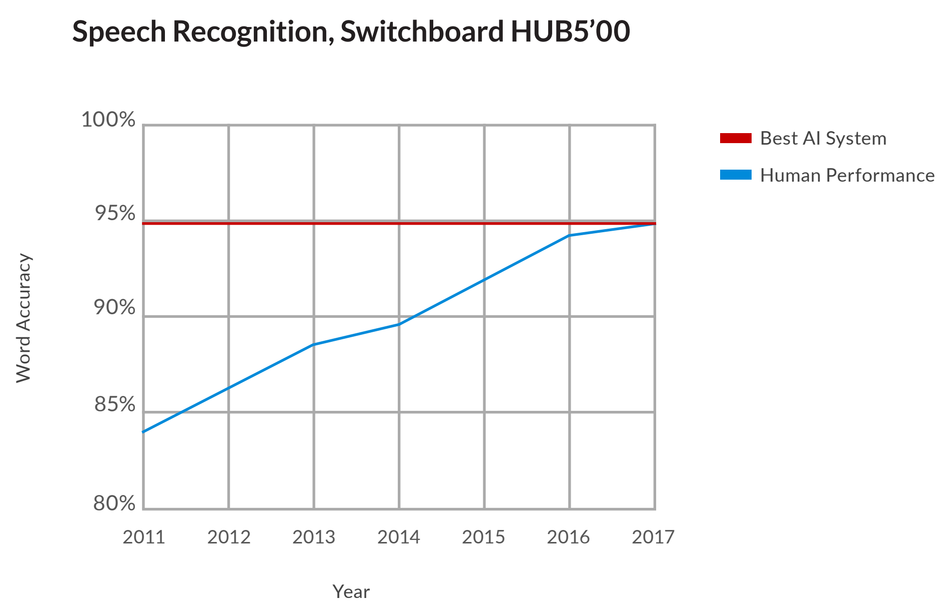

Figure12: Speech Recognition vs. Human on Switchboard HUB5'00 Dataset

Appendix C: Acronyms Used in this Report

Acronym	Term
ADE	Adverse Event
AMCs	Academic Medical Centers
ANN	Artificial Neural Network
ASR	Automatic Speech Recognition
BI	Business Intelligence
CAC	Computer Assisted Coding
CAPD	Computer Assisted Physician Documentation
CCD	Continuity of Care Document
CCE	Clinical Concept Extraction
CDI	Clinical Documentation Improvement
cTAKES	Text Analysis and Knowledge Extraction
CTM	Clinical Trial Monitoring
CUI	Concept Unique Identifier
DBN	Deep Belief Network
DL	Deep Learning
DNR	Drug Name Recognition
DOS	Data Operating System
EDW	Enterprise Data Warehouse
EHR	Electronic Health Record
ELT	Extract Load Transform
ETL	Extract Transform Load
FDA	Food and Drug Administration
GSC	Gold Standard Corpora
HCC	Hierarchical Condition Category
HCOs	Healthcare Organizations
HIE	Health Information Exchange
HIT	Health IT
HMM	Hidden Markov Models
LHS	Learning Health System
LSA	Latent Semantic Analysis
LSTM	Long Short-Term Memory
MedLEE	Medical Extraction and Encoding
MIPS	Merit-based Incentive Payment System
ML	Machine Learning
NER	Named Entity Recognition
NLPaaS	Natural Language Processing as a Service
NLPOS	Natural Language Processing Operating System
NLQ	Natural Language Query
NLU	Natural Language Understanding
NN	Neural Network
PHM	Population Health Management
PPC	Payer Provider Convergence
PPV	Positive Predictive Value
RA	Risk Adjustment
RNN	Recurrent Neural Network
ROI	Return on Investment
SaaS	Software as a Service
SL	Supervised Learning
SNOMED-CT	Systematized Nomenclature of Medicine–Clinical Terms
STS	Semantic Textual Similarity
SVM	Support Vector Machine
UIMA	Unstructured Information Management Architecture
UMLS	Unified Medical Language System
VBC	Value-Based Care
VPAs	Virtual Personal Assistants
WAcc	Word Accuracy
WER	Word Error Rate

Endnotes

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