Better technology leads to better coding

Natural language processing with Optum™ LifeCode®

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Coding is in the middle of a five-year storm. In 2008, Medicare Severity DRGs (MS-DRGs) nearly doubled the number of DRGs and made severity of illness a more important revenue distinction. On its heels came Medicare's Recovery Audit Contractor (RAC) initiative, which led an array of federal audit programs determined to take back inappropriate reimbursement. Finally, at the eye of the storm is ICD-10-CM/PCS, which by October 1, 2013 will completely change the way coders code diagnoses and procedures.

Existing coding tools aren't enough anymore. Coding software advances from the 1990s and 2000s—encoders, editors, groupers, etc.—have helped HIM departments increase productivity and revenue, but may no longer be able to deliver incremental efficiencies. More advanced coding technologies such as computer-assisted coding (CAC) and natural language processing (NLP) have matured to the point where they can help provider organizations weather the regulatory storm.

After more than a decade on the market, CAC and NLP have combined to become a viable enterprise solution for inpatient, outpatient, and professional settings. Because CAC can—within seconds—read and interpret an entire documentation set and recommend a short list of codes, health care providers can utilize the technology to increase coder productivity, improve coding accuracy, and enhance coding compliance while decreasing time to revenue, administrative costs, and denials due to inaccurate coding. But CAC software is only as good as the NLP technology it uses. This paper explores why NLP is the most critical variable for CAC to keep its promise of saving organizations time and money.

NLP: A technology category with a variety of approaches

NLP is technology that scans and interprets narrative text. With NLP, information included in clinical documents can be transformed into discrete, meaningful pieces of information.

NLP as a term identifies a set of technologies and approaches, each of which vary in terms of their effectiveness. All NLP technologies available today for CAC fall into one of five methods:

- **Medical Dictionary Matching:** Matches individual words or groups of words found within the documentation to standard terminology from a medical dictionary. For words that match, the text is typically highlighted and validated by the coder.
- **Pattern Matching:** Extends the capabilities of medical dictionary matching by coordinating terms with specific patterns of text that describe a diagnosis or a procedure.
- **Statistical:** Gathers information from a large, pre-coded sample of documents to train algorithms based upon word and pattern distributions
- **Symbolic Rules:** Analyzes language using rules or lexicons,[1] identifying the elements of language with symbols that can be manipulated by the system.
- **Symbolic Rules and Statistical Components:** Utilizes both symbolic NLP and a mathematical model of linguistics, including semantics (levels of language that contribute to meaning) and pragmatics (applying domain knowledge to recognize information in the correct context).

To understand how these methods differ, we need to define the standard measurements of NLP accuracy:

- **Precision** measures the number of accurate results compared to total results. Higher rates of precision mean lower false positives.
- **Recall** measures the number of accurate results compared to the potential number of accurate results. Higher rates of recall mean lower false negatives (or missed codes).

Medical dictionary matching NLP typically produces the highest number of medical terms highlighted as potential codes. Precision of medical dictionary matching is very low, due to the low number of accurate hits compared to the high number of total hits. This method does little to enhance coder productivity, since coders are left to sift through many false positives to find accurate codes.

Pattern matching NLP has better precision than medical dictionary matching, returning fewer false positives. But because it can't analyze the meaning and subtleties of language, it has somewhat lower recall than medical dictionary matching. Neither medical dictionary nor pattern matching techniques include the intelligence to apply coding guidelines to their analysis.

Statistical NLP relies on a large sample of documents where the meaning of the language has already been matched to accurate results. Only then can the training algorithm start to perform its analysis, form word-type distributions, and derive correlations between input and results that the statistical NLP can apply. Statistical NLP systems can often be trained quickly to a moderate level of recall and precision, but high performance can be limited by the availability of a highly accurate training sample and the need to have a large number of examples of each specific coding scenario.

Symbolic rules NLP uses inference rules to interpret meaning from text, therefore yielding high precision rates (fewer false positives). Symbolic rules introduce more sophisticated techniques for analyzing medical language based upon parsing phrases and sentences. Experts in linguistics construct symbolic rules based upon parts of speech and standard English syntax.

[1] Liddy, E.D. "Natural Language Processing." *Encyclopedia of Library and Information Science*, 2nd Ed. New York City. Marcel Decker, Inc., 2003.

A medical condition or procedure is recognized when one or more rules successfully match a portion of the clinical documentation. Symbolic rules support more advanced language recognition, but become very difficult to maintain for large code sets like ICD-9 and ICD-10.

Symbolic rules with statistical components is a patented NLP method used in Optum™'s LifeCode® NLP engine. LifeCode has sophisticated inference rules that allow it to "understand" how documentation relates to coding rules, enabling it to, among other things, correctly assign combination codes, recognize related symptoms, or differentiate personal versus family history. LifeCode integrates its symbolic analysis with a knowledgebase that consists of more than 10 million medical facts, which allows for consistent interpretation of clinical content. LifeCode presents coders with codes that are highly precise and that exhibit a high amount of recall.

LifeCode is the only patented NLP technology on the market today. In fact, LifeCode is distinguished by two patents. The original patent—secured in 2005—describes "vector processing," LifeCode's mathematical model for isolating, comparing, and assigning different facts from clinical documentation to build a contextual framework.

In 2011, Optum360™ was awarded another LifeCode patent, which describes "mere-parsing," LifeCode's method for determining meaning from free text. Parsing is defined as the syntactic analysis of words to determine grammatical structure. Mere-parsing is the process by which LifeCode assigns meaning using not just single phrases within a sentence, but also to a combination of related phrases from throughout the documentation.

LifeCode is a unique, mature NLP that has been on the market for more than a decade. Its first commercial use was in a professional setting—part of the Optum CAC solution. The same LifeCode NLP is used in the Optum CAC inpatient solution, which was launched in 2008.

Meeting the ICD-10 challenge with Optum CAC and LifeCode

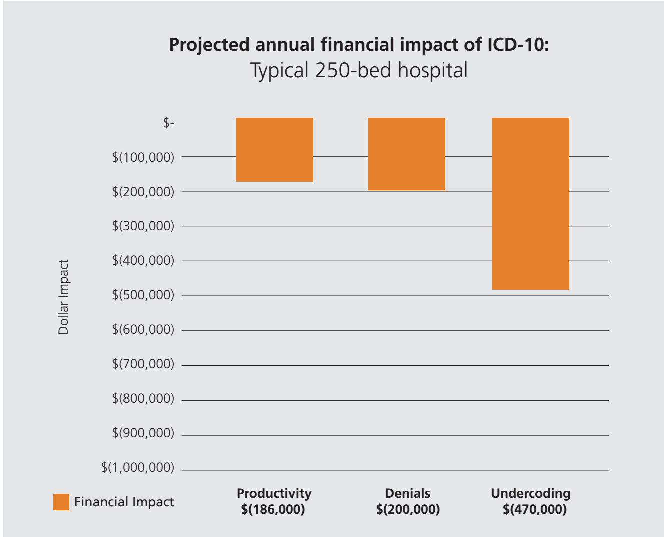
Understanding the differences in NLP engines can help organizations choose the CAC technology that meets their unique needs. As they choose, however, they would do well to consider the elephant in the room: ICD-10.

ICD-10 is looming larger on the horizon, and HIM leaders are right to be fearful of its potential effects. Based on Canada's experience with their own ICD-10 conversion, productivity loss percentage estimates range from 10 to 25 percent[2] to up to 50 percent.[3] Productivity isn't the only element that will suffer.

ICD-10's greater specificity and the sheer volume of codes it contains will lead to less accurate coding and more denied claims. In the ICD-10 final rule, the U.S. Department of Health & Human Services estimated that denied claims would at least double from a current average of three percent to a level of six to 10 percent.[4]

Combining data from recent industry reports,[5,6,7] we can estimate that because of ICD-10, an average 250-bed hospital can expect to take a financial hit of as much as $850,000 in 2014. This is due to lost productivity, denied claims, and undercoding (see Figure 1).

Figure 1: Projected annual financial impact of ICD-10: Typical 250-bed hospital



HIM staffing is also an ICD-10 concern. Considering the ongoing shortage of coders[8] and the general assumption that some coders will retire rather than learn an entirely new code set,[9] HIM directors may be wondering how long their coding backlogs will become after October 1, 2013.

Estimated productivity and claims denial losses assume that health care providers will not make mitigating operational changes. However, sophisticated CAC/NLP combinations such as Optum CAC/LifeCode are positioned to be a strong moderator of the effects of ICD-10 and can help organizations avoid the brunt of the financial challenges it poses.

With its superior precision, the LifeCode NLP technology can maintain and even enhance productivity at the ICD-10 conversion when compared to current coding methods. Coders will be required by ICD-10 to find codes based on highly granular elements: laterality, severity, acuity, exact body part affected, etc. Poring over documentation, especially in a hybrid record from multiple sources (electronic and otherwise), will take even more time for coders using the ICD-10 code set. LifeCode NLP's ability to scan and interpret an entire documentation set within seconds will help alleviate the productivity challenges of ICD-10.

LifeCode NLP, with its superior recall, can help alleviate concerns about undercoding and missed charges. The volume of code choices may make it difficult to find the correct code. In many cases, there will be varying degrees of "correct," with the most specific generally being the most accurate. A coding reference search may help coders find a code that may seem like a good fit for a diagnosis, but there may be more specific codes that are a better match. The LifeCode NLP compares relevant phrases from the documentation with a growing knowledgebase that now includes more than 10 million pieces of information, resulting in a more focused list of codes from which a coder can choose the most appropriate.

In preparation for ICD-10, Optum360 is committing the resources to deliver ICD-10 CAC capabilities one year in advance of the October 1, 2013 deadline. Optum CAC clients who also have an ICD-10 MS-DRG grouper will be able to use real-life scenarios based on current case mix to conduct their ICD-10 coder training.

[2] *Replacing ICD-9-CM with ICD-10-CM and ICD-10-PCS: Challenges, Estimated Costs and Potential Benefits*. Simsbury, CT: Robert E. Nolan

[3] "Implementing ICD-10: A Canadian Perspective from the Front Line," *Revenue Cycle Strategist*, 2009. p. 3. http://www.hfma.org/Publications/Newsletters/Revenue-Cycle-Strategist/Archives/2009/February/Revenue-Cycle-Strategist--February-2009-Issue/.

[4] Department of Health and Human Services. "HIPAA Administrative Simplification: Modification to Medical Data Code Set Standards To Adopt ICD-10-CM and ICD-10-PCS; Final Rule." *Federal Register* 74:11 (16 January 2009) p. 3346. http://edocket.access.gpo.gov/2009/pdf/E9-743.pdf.

[5] Replacing ICD-9-CM with ICD-10-CM and ICD-10-PCS, pgs. 21-22.

[6] Libicki, Martin C. and Irene T. Brahmakulam. *The Costs and Benefits of Moving to the ICD-10 Code Sets*. Santa Monica, CA: RAND Corporation, 2004. http://www.rand.org/pubs/technical_reports/TR132.

[7] Financial Leadership Council. ICD-10 *Transition Success: Launching a Focused and Coordinated Plan Grounded in Expertise.* Washington, D.C.: The Advisory Board Company, 2011. p. 4. http://www.mhei.org/programs/documents/ICD-10web.pdf.

[8] Bronnert, et al. p.2.

[9] Sullivan, Tom. "Will ICD-10 Spark Coder Chaos?" *ICD-10 Watch* (blog), 24 May 2010. http://www.icd10watch.com/blog/will-icd-10-spark-coderchaos.

Less sophisticated NLP technologies may struggle with ICD-10's sheer volume of data. Statistical NLP, for example, requires large amounts of accurately coded and annotated medical records for training. To cover ICD-10, statistical NLP will require a huge amount of data to describe all possible coding scenarios for 155,000 codes. Additionally, with statistical NLP, there is typically a trade-off between precision and recall—increased recall at the expense of lower precision or better precision with subpar recall. One can see statistical users suffering through significant growing pains before reaching even moderate levels of ICD-10 accuracy. Pattern matching NLPs will see similar complications, since accounting for all the specific patterns of documentation for all ICD-10-CM/PCS codes will be a monumental challenge. As for medical dictionary matching NLP, its low level of precision will give coders a much longer list of choices through which they must comb to find the correct ICD-10 code.

Natural language processing can enhance coder workflow

Understanding the precision and recall of the various NLP technology choices as well as NLP's impact on ICD-10 preparation can help answer key questions about what the potential CAC has for improving HIM results. But HIM leaders need to worry about operational questions as well. How will CAC impact coder workflow? And then there's the question that's likely in the back of every coder's mind: Will CAC replace coders?

Let's dispense with the replacement question first: NLP technology has made significant strides in the past decade, but the experienced judgments of coders will remain essential to the process. It is true that Optum CAC's professional version—for some simple procedures—can analyze, code, and send cases to billing without intervention from a traditional coder. But the complexity of both inpatient and outpatient encounters and the common use of hybrid records require human expertise to ensure finalized codes are complete and accurate.

Auditing CAC output will be a critical role for coders and coding managers.

According to an AHIMA-sponsored CAC committee, coders and coding managers will transition into "coding editors" and "coding analysts," respectively.

> In automated workflow environments, the current [coder] role evolves to a clinical coding editor. Rather than assigning codes and entering them into computers, the technology now suggests codes for confirmation. The traditional role of the coding manager becomes a hybrid of clinical coding analyst, process improvement engineer, and terminology asset manager.[10]

An automated workflow environment involving CAC brings with it significant process improvements. Table 1 highlights the difference between the typical workflow of a coder using multiple record systems and the workflow of a coding editor with Optum CAC providing the automated workflow.

In the coder workflow example, coders must log on to multiple systems and switch back and forth between those systems to gather needed information. If one system times out or crashes, coders are stuck waiting for the system to come back online. And if the case needs review, it must be recoded, essentially, since there is no other way to determine where the supporting documentation for the chosen codes is found.

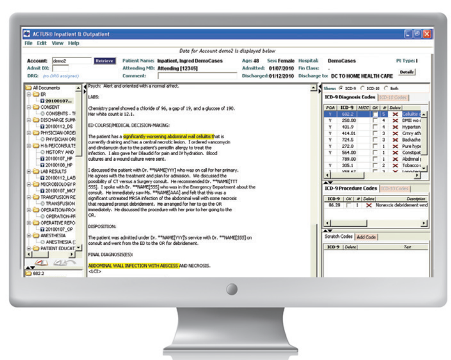
[10] Bronnert, June, et al. "Transitioning Coding Professionals into New Roles in a Computer-Assisted Coding Environment," *CAC 2010-11 Industry Outlook and Resources Report*. Chicago: AHIMA, 2011. p.4.

Table 1: Coder workflow

Coder workflow using multiple record systems and an encoder	Coding editor workflow using Optum CAC and an encoder
1. Select case for coding 2. Go to document management system(s) to review transcribed documents, begin reading history and physical documents 3. Go to scanned image system to begin reviewing scanned images of Progress Notes; realize lab work needs to be checked 4. Check lab information system 5. Go to scanned image system; continue reading Progress Notes 6. Go to document management system to read operative notes 7. Repeat process until all documentation required for coding has been reviewed 8. Go to encoder and enter codes 9. Screen scrape encoded data into billing system 10. Go to billing system to "final bill" case	1. Select case for coding 2. Go to Optum CAC to review all text and scanned image documentation required for coding and NLP suggested codes 3. Interface with encoder where needed for code lookups and DRG optimization 4. Review and validate all coding results 5. Coding information is sent to billing system

When working in Optum CAC, coders-turned-coding-editors see a clean, usable interface that supplies them with all the documentation they need in one application (see Figure 2). On the right side of the page, the coding editor sees the list of codes suggested based on LifeCode's thorough review of the entire case documentation. One code is highlighted. On the left side of the screen, the coding editor sees the document from which LifeCode determined the highlighted code, with emphasis on the precise language that relates to the code. In another column on the left side of the screen, coding editors have instant access to every document related to the case.

Figure 2: Optum CAC screen shot



Optum CAC simplifies the documentation review process by consolidating the view of the patient case for both electronic and scanned documents. The coder-turned-coding-editor only needs one system logon. In addition, all chosen codes are linked to the source documentation, providing full traceability. This traceability makes any secondary review or audit process less time-consuming and more manageable, which helps health care providers spend less money on DRG review.

In a CAC environment, the HIM directors may want to adjust the way they approach their coding department. The degree to which their departments achieve increases in productivity and accuracy will be directly dependent on the degree with which directors successfully manage change. Acceptance of change and embracing new processes are key expectations that should be set at the start of any CAC implementation. Developing accountability processes and incentive programs will help directors to ensure that CAC lives up to its promise.

Patented LifeCode NLP method gets results in both inpatient and outpatient settings

Clients have leveraged both Optum CAC inpatient and outpatient versions to gain impressive results.

Productivity gains: UPMC Health System, a 20-hospital integrated delivery network, was Optum's development partner and first customer for the Optum CAC inpatient solution.11 They installed Optum CAC in December of 2008, after which they saw an overall 21 percent increase in the number of inpatient charts coded per hour. Another way of looking at this productivity increase is this: five coders-turned-coding-editors working in Optum CAC could do the work of six coders working in their legacy coding system.

In addition, UPMC hospitals saw a significant overall decrease in the amount of overtime their coders had to work—66 percent. HIM directors know that a large portion of their operating budget comes from staffing. To be able to cut overtime by two-thirds represents a considerable savings.

Another recent client, OhioHealth, is an eight-hospital integrated delivery system located in central Ohio. They installed the Optum CAC solution for diagnostics in June 2010 in five of their eight hospitals, while the Optum CAC emergency department solution was installed in those same hospitals in January 2011. These installations helped OhioHealth gain a 106.5 percent increase above their average diagnostic coder productivity standard and a 91.7 percent increase above their average ED coder productivity standard. These increases have compelled OhioHealth to set new, more aggressive coder productivity standards.[12]

Overall, coders at these hospital systems were able to get more work done in less time.

Improved case mix index: UPMC also saw an increase in their overall case mix index (CMI). Before Optum CAC installation, their Medicare CMI averaged 2.06. Two years after installation, their Medicare CMI averaged 2.25, an increase of eight percent. UPMC estimated a positive revenue impact of about $950 per Medicare case—total annual revenue impact due to the increased CMI was estimated to be $22 million annually.

A note about CMI: The more thorough documentation review that NLP can provide often yields a higher CMI. But many factors affect case mix—a strong documentation improvement program or new services being provided by the organization, for instance. Other factors are outside of an organization's control. UPMC saw a dramatic increase in case mix after using Optum CAC with LifeCode NLP. Depending on the state of a system's documentation program, those results may not be typical.

But Optum CAC has displayed remarkable abilities to improve case mix even in organizations that have taken previous steps to increase CMI. Gwinnett Hospital System, Atlanta, had already benefited from a robust documentation improvement program when they installed Optum CAC in September 2010. Gwinnett leaders anticipated only a modest one percent CMI increase after CAC implementation. However, as of July 2011, Optum CAC has helped them improve CMI by an additional 3.3 percent.

Improved coding quality: Like many other institutions, UPMC uses external auditors to determine the quality of their coding. In 2008, they spent more than $800,000 on coding audits. Following their CAC implementation, they saw a decrease in external auditor recommendations of more than 50 percent, and as a result, their reliance on external auditors also decreased. UPMC saved more than $500,000 in yearly audit fees after installing Optum CAC.

Early on in the implementation process, internal UPMC reviewers also saw a difference between the coding accuracy of hospitals using CAC and the hospitals that weren't yet implemented. At the hospitals using Optum CAC, DRG reviewers agreed with coder results 95 percent of the time. At one non-CAC hospital, the rate of agreement was only 89 percent while at another non-CAC hospital, the rate was just 84 percent.

Conclusion: Advanced LifeCode NLP is key for improving coding performance

The promise of CAC is increasing coding productivity, boosting overall coding quality and consistency, and making the coding process more transparent and auditable. Natural language processing technology is the key ingredient for ensuring the promise of CAC is kept. Choosing software with a sophisticated NLP engine that doesn't merely match words can mean the difference between a strong return on your CAC investment or a weak one—or perhaps none at all.

Certainly, there is no panacea for improving HIM departments. Software alone won't solve every challenge. We have found that an implementation plan that includes an appropriate amount of training, change management, and follow up yields the most CAC success. A culture of performance and accountability in the coding department certainly helps. But choosing software that matches your needs and that exhibits a strong track record is essential. As we've seen, Actus CAC with LifeCode NLP is a strong solution for improving HIM performance and operations, as well as for mitigating the impacts of the ICD-10 conversion.

To learn more about CAC, NLP, and Optum solutions, call 866.322.0958 or email perform@optum.com.

Find out more at optum.com/EnterpriseCAC.

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Optum360 is a leading provider of patient-centered and client-focused revenue cycle services. With a comprehensive suite of technology, content and services, Optum360 is helping modernize health care financial transactions to make navigating the health system and understanding medical costs simpler and more transparent and intuitive for everyone.

[11] All UPMC statistics contained herein can be attributed to Nancy Soso and Adele Towers. "Inpatient Computer-Assisted Coding at an Academic and Community Medical Center." 2010 AHIMA Convention and Exhibit. Orlando, Florida. 28 September 2010.
[12] Setty, Diane. "From Selection to Results." OptumInsight CAC Webinar Series. 16 May 2011.

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