



Predictive Analytics and Decision-Support for Improving Patient Care

C. Martin Harris, M.D.
Chief Information Officer, Cleveland Clinic
Executive Director, eCleveland Clinic

Acute Care Reimbursement History

Medicare

Timeframe

1965 - 1982

1983 - Present

2014 - Future

**Reimbursement
Models**

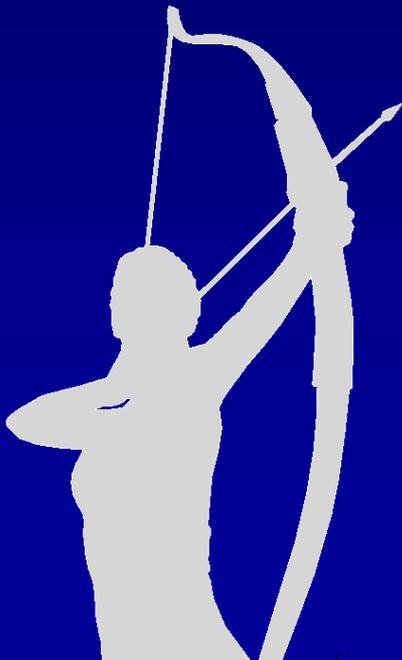
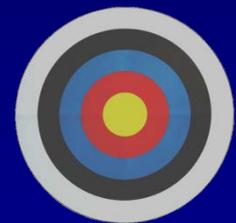
Cost +

IPPS or DRG

**All Inclusive
Risk-based**

CMS Three Part Aims for Healthcare Delivery System Improvement

- **Better care for individuals through seamless coordinated health care**
- **Reduced costs through continuous improvement**
- **Better health for populations**



Definitions

BIG Data / Decision Support/ Predictive Analytics

Definitions

BIG Data / Decision Support/ Predictive Analytics

“Big data is high-volume, -velocity and -variety information assets that demand cost-effective, innovative forms of information processing for enhanced insight and decision making.”

Svetlana Sicular
Research Director

Gartner[®]

Definitions

BIG Data / Decision Support / Predictive Analytics

Decision Support is the rapid, algorithmic analysis of retrospective and real-time data for reducing variation in clinical decision making.

Definitions

BIG Data / Decision Support/ Predictive Analytics

Predictive analytics is a forward-looking, rapid analysis approach to data mining that emphasizes prediction rather than classification to suggest the clinical challenges of the future.

Data

Definitions

BIG Data / Decision Support/ Predictive Analytics



Data

Machine-Reasoning
Definitions
Decision Support/ Predictive Analytics



Decision Support

Predictive Analytics

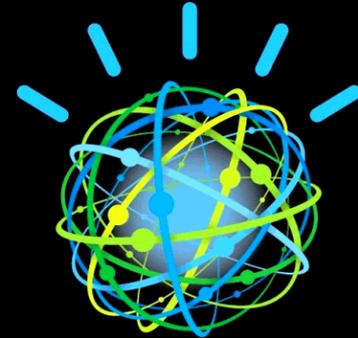


Data

Machine-Reasoning



Predictive Analytics



IBM WATSON

 Cleveland Clinic

Watson

Medical Research Agenda

Build and demonstrate a Clinical Decision

Support software system having the following progressive, step-wise capabilities:

- Healthcare System Physiology
- Care Management and Coordination
- Selected Diagnostics and Treatment Skills:
To map *factors* (bits of patient data) to *probable diagnoses* through justifiable *evidence* collected from background content and/or through user interaction. To map *factors* and *probable diagnoses* to appropriate *treatment options* through justifiable *evidence* collected from background content and/or through user interaction
- How to do Continuous Medical Education

Cleveland Clinic Use Cases

- ← Utilization Management and other Administrative Tasks
- ← Clinical Process Monitoring
- ← Clinical Diagnosis and Treatment Decision Support
- ← Watson goes to Medical School

Watson

Goals / Progress Matrix

How to do
Continuous
Medical Education

- **Specialized medical content**
 - Internal journals, ontology, coding system, etc.

Selected
Diagnostics and
Treatment Skills

Care Management
and Coordination

Healthcare System
Physiology

Utilization
Management and
other Administrative
Tasks

Clinical Process
Monitoring

Clinical Diagnosis
and Treatment
Decision Support

Watson goes to
Medical School

Watson

Goals / Progress Matrix

How to do
Continuous
Medical Education

Selected
Diagnostics and
Treatment Skills

Care Management
and Coordination

Healthcare System
Physiology

- **Expertise:**
 - **Cleveland Clinic will provide:**
 - Expert (human) annotators and annotations
 - Use case definition and development with practitioners
- **Diagnostic and Treatment Process**
 - Vetted Input and Output pairs, along with vetted Evidence

Utilization
Management and
other Administrative
Tasks

Clinical Process
Monitoring

Clinical Diagnosis
and Treatment
Decision Support

Watson goes to
Medical School

Data

Machine-Reasoning



[Google.org home](#)

[Dengue Trends](#)

Flu Trends

[Home](#)

United States ▾

National ▾

[Download data](#)

[How does this work?](#)

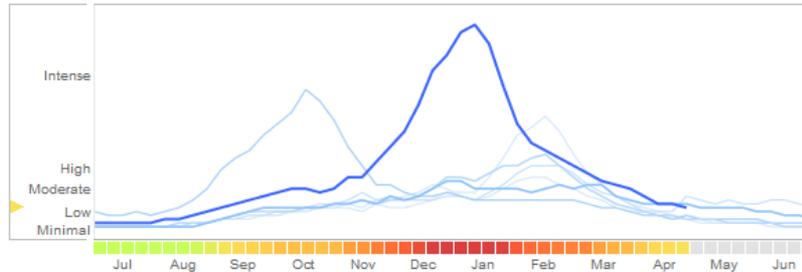
[FAQ](#)

Explore flu trends - United States

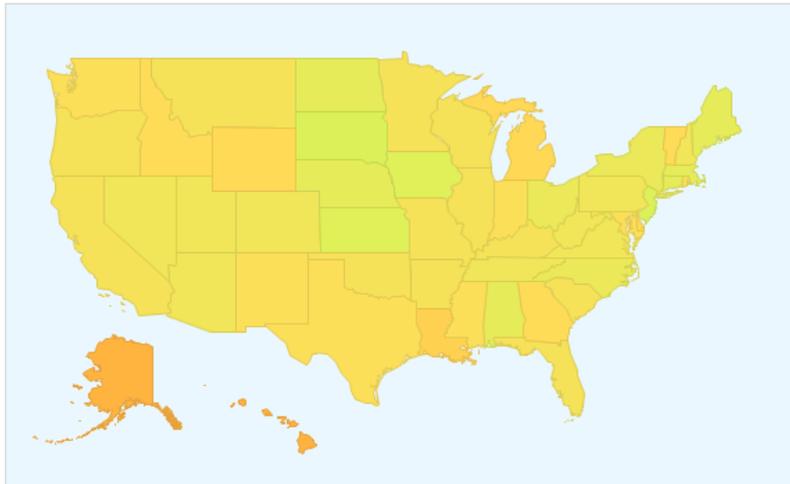
We've found that certain search terms are good indicators of flu activity. Google Flu Trends uses aggregated Google search data to estimate flu activity. [Learn more >](#)

National

● 2012-2013 ● Past years ▾



States | [Cities](#) (Experimental)



Estimates were made using a model that proved accurate when compared to historic official flu

Each week, millions of users around the world search for health information online.

We have found a close relationship between how many people search for flu-related topics and how many people actually have flu symptoms.

We compared our query counts with traditional flu surveillance systems and found that many search queries tend to be popular exactly when flu season is happening.

By counting how often we see these search queries, we can estimate how much flu is circulating in different countries and regions around the world.

The New York Times

FEBRUARY 24, 2013, 11:00 AM 4 Comments

Disruptions: Data Without Context Tells a Misleading Story

By NICK BILTON



Erik S. Lesser/European Pressphoto Agency

Google's Flu Predictor overestimated how many people had the flu this flu season

f FACEBOOK

t TWITTER

g+ GOOGLE+

SAVE

E-MAIL

SHARE

PRINT

Several years ago, [Google](#), aware of how many of us were sneezing and coughing, created a fancy equation on its Web site to figure out just how many people had influenza. The math works like this: people's location + flu-related search queries on Google + some really smart algorithms = the number of people with the flu in the United States.

So how did the algorithms fare this wretched winter? According to [Google Flu Trends](#), at the flu season's peak in mid-January, nearly 11 percent of the United States population had influenza.

Yikes! Take vitamins. Don't leave the house. Wash your hands. Wash them again!

But wait. According to [an article in the science journal Nature](#), Google's disease-hunting algorithms were wrong: their results were double the

According to an article in the science journal *Nature*, Google's disease-hunting algorithms were wrong: their results were double the actual estimates by the Centers for Disease Control and Prevention.

Scientists have a theory about what went wrong. Google's algorithm was looking only at the numbers, not at the context of the search results.

In today's digitally connected world ... almost everything we touch is part of a larger data set.

But the people and companies that interpret the data may fail to apply background and outside conditions to the numbers they capture.

Now, as we enter a world of big data, we have to learn how to apply context to these numbers.

The New York Times

FEBRUARY 24, 2013, 11:00 AM 4 Comments

Disruptions: Data Without Context Tells a Misleading Story

By NICK BILTON



Erik S. Lesser/European Pressphoto Agency

Google's Flu Predictor overestimated how many people had the flu this flu season

f FACEBOOK

t TWITTER

g+ GOOGLE+

SAVE

E-MAIL

SHARE

PRINT

Several years ago, [Google](#), aware of how many of us were sneezing and coughing, created a fancy equation on its Web site to figure out just how many people had influenza. The math works like this: people's location + flu-related search queries on Google + some really smart algorithms = the number of people with the flu in the United States.

So how did the algorithms fare this wretched winter? According to [Google Flu Trends](#), at the flu season's peak in mid-January, nearly 11 percent of the United States population had influenza.

Yikes! Take vitamins. Don't leave the house. Wash your hands. Wash them again!

But wait. According to [an article in the science journal Nature](#), Google's disease-hunting algorithms were wrong: their results were double the

According to an article in the science journal *Nature*, Google's disease-hunting algorithms were wrong: their results were double the actual estimates by the Centers for Disease Control and Prevention.

Scientists have a theory about what went wrong. Google's algorithm was looking only at the numbers, not at the context of the search results.

In today's digitally connected world ... almost everything we touch is part of a larger data set.

But the people and companies that interpret the data may fail to apply background and outside conditions to the numbers they capture.

Now, as we enter a world of big data, we have to learn how to apply context to these numbers.

Data

Machine-Reasoning

Policy Implications



Implication
1

Implication
2

Judgement:

When presented with multiple options, who or “what” makes the choice?

Responsibility

When a decision is made based on a computer-performed analysis, who ultimately, is accountable for the outcome?

Data

**Machine-
Reasoning** **Data** **Policy**
Implications

**Machine-
Reasoning**

In an era of ever-increasing data availability, analytic capability, and machine-based reasoning and action, policy leadership becomes ever-more important to achieve intended outcomes.

**Machine-
Guided
Action**
Judgement:

**Analytic
Tools**

Data

In an era of ever-increasing data availability, analytic capability, and machine-based reasoning and action, policy leadership becomes ever-more important to achieve intended outcomes.

Machine-Guided Action

Analytic Tools

Machine-Reasoning

Policy



Cleveland Clinic

Every life deserves world class care.