How Data Affects Decision

By TANAY GAHLOT[*]

Whats the point in storing data?To make decisions. Due to advances in communication technology, data can be transferred quickly, stored economically and analyzed efficiently. All of the above has lead to development of Reality Mining, Freakonomics(Stephen J. Dubner 2005), Personal Analytics, Advanced Disaster recovery solution, Social Network analysis, Human Dynamics(Pentland n.d.a), Social Sensing(Olguin and Pentland n.d.), Computational Social science(David Lazer and Alstyne n.d.) and many more fields. Majority of companies have special division dedicated to analytics which try to predict cost and benefits of decision. Governance has moved to E-Governance. Battle field is becoming analytical since information is the key to win war. Mobile phones are now Smart Phones because of their computational power. City planning is done taking into considering past data. Marketing is done at a never before scale and efficiency. All decision in personal life are tested against data, even as personal a decision as Bunking a class is taken by consulting bunk affordance(Tanay Gahlot n.d.). Lets us jump into world of data empowered decision.

Can Human behaviour be modelled computationally?Can we come up with application that could make smarter decision than we do?Can we predict the outcome of social situation?Lets have a deeper look at science behind human behaviour.

I. Honest Signal and Personal Analytics

Honest signals(Pentland 2008) are parameter that humans cant fake without special training therefore they make up excellent measure of human behaviour. These signals have immense potential to predict outcome of social situation like date, interview, project proposal, negotiation etc. These signals are result of extensive study done at MIT media lab by Prof. Alex Sandy Pentland, director of Human dynamics(Pentland n.d.*a*) group.

What are Honest Signal?

- Influence: The amount of influence each person has on another in a social interaction. Influence is measured by the extent to which one person causes the other persons pattern of speaking to match their own pattern.

[*] Gahlot: NIT Goa, Dhavali Ponda Goa, tanaygahlot@gmail.com

- Mimicry: The reflexive copying of one person by another during a conversation, resulting in an unconscious back-and-forth trading of smiles, interjections, and head nodding during a conversation.
- Activity: Increased activity levels normally indicate interest and excitement, as seen in the connection between the activity level and excitement in children, or when male orangutans shake branches in order to impress potential mates.
- Consistency: When there are many different thoughts or emotions going on in your mind at the same time, your speech and even your movements become jerky, unevenly accented and paced. The consistency of emphasis and timing is a signal of mental focus, while greater variability may signal an openness to influence from others.

Humans can sense these signals unconsciously and make decision based on that. These signals were used in predicting the outcome of business plan pitching competition at MIT Sloan school of Business. By using camera and audio recorder embedded into a device known as sociometer(Olguin and Pentland n.d.) they were able to predict the outcome of competition with correlation r=0.6 and probability p¡.01

People in real-life situations employ combinations of honest signals rather than using them individually. These combinations cluster in characteristic ways to signal the social role that the person has adopted the attitudes, intentions, and goals that characterize typical types of relationships between people. To illustrate how honest signals communicate social roles, I will start with the central interpretation of each of our honest signals. Lets say that influence signals attention, mimicry signals empathic understanding, activity level signals interest, and consistent emphasis signals mental focus and determination (and hence inconsistent or variable emphasis signals a possible openness to influence). Because people have this capability for automatic signaling and response, the signaling of each person can propagate through the chains of people that make up their social network, eventually changing the behavior of the entire group. So when a group of people gets together, we need to consider not just the individual behaviors but also the social circuits formed by the patterns of signaling between them. These social circuits specify networks of dominance, obligation, friendliness, attention, and receptivity, which in turn coordinate the day-to-day behavior of the group. Honest signals have evolved to coordinate individual behaviors in the midst of competition. In groups, though, competition is not just a one-on-one situation. There are instead competing coalitions supporting different alternatives, with the membership of the coalition shifting with each different question or new idea. Consequently, participants take on many different roles in quick succession, each with its own characteristic signaling display How did primitive humans make group decisions? With only limited language skills, the decision process couldn'tt really involve logical argument. For that matter, how do ape groups decide what to do? With language removed from the equation, some way must still exist to gather and assess the possibilities for group action, and make group decisions that maximize rewards and minimize risk. There also has to be a way for each individual to know what the group decided, so that everyone can play their respective roles. This evolutionary advantage would result in the selection of the types of network intelligence that produced the most accurate and reliable decision making. As such, the signaling and circuitry that occur in primitive human groups may tell us a great deal about what sorts of group decision making we are naturally good at and how to promote effective decision making in modern-day organizations. What controls the pattern of communication within the social network? Within a face-to-face meeting, attention and interest, signaled by influence on the conversational turn taking and activity level, are critical in shaping the pattern of communication. People who are paying attention to each other tend to coordinate their activities (which we can measure as influence), and people who are interested spend more time talking together (a measure of activity). Consequently, people who are working together are more likely to stop to talk in the hall, go for lunch, get coffee, go out for a drink, and so forth, thereby influencing each others pattern of communication.

Device that people at MIT Media lab(n.d.) came up with to measure these signals was Sociometer(Olguin and Pentland n.d.). A sensor-based feedback system for organizational computing consists of environmental and wearable sensors, computers, and software that continuously and automatically measure individual and collective patterns of behavior, identifies organizational structures, quantifies group dynamics, and provides feedback to its users. The purpose of such a system is to improve productivity, efficiency, and/or communication patterns within an organization. The Sensors that were used in making Sociometer are available in Present day Smart Phones. This idea has tremendous app potential in personal, organization and group sensing application. With google glass(Google n.d.) about to launch in 2014, developer are pacing to come up with app that are compatible with glass. Glass opens possibility of new range of application that were not possible with mobile phone. With the power of computation combined with wearable gadget reality mining(Pentland n.d.*b*) is becoming more real.

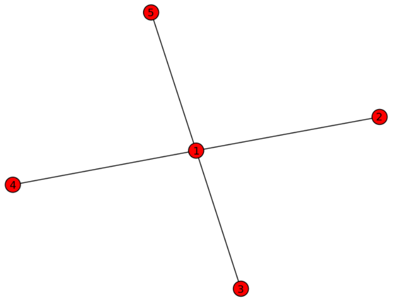
II. Social Network Analysis

Can we computationally answer "Who is the most important person in my life?"?Can we predict the outcome of our comment to a post?Can we identify the most resourceful person in my network for a particular task? Social Network Analysis(SNA)(Tsvetovat n.d.) is a sub-branch of network science(Barabasi n.d.), it deals with networks involving people as nodes and their relationship as edges. Social network can exist in very well defined scenario such as Facebook, LinkedIn, Twitter and Google+ or classroom ,workplace and family, which are not well defined. Relationship could be asymmetric, symmetric, weighted, non-weighted, random, preferential etc. These network comes to life in social situation and interaction. They play a significant role in deciding the outcome of social situation. This is what makes the analysis of such network very interesting. These network also determine the flow of information through a network. This is of special interest to Advertiser who wants to pitch their idea to a person who is interested and well placed in his network to spread the information.

Degree Centrality: One of the first questions one asks when looking at a social network is who is more important in this network?, or who has the power?

Every community has its own Paris Hiltons and Lady Gagaspeople who are significantly more popular then others. There are usually very few of them, and they are orders of magnitude more popular then everyone else. In order to quantify it we use degree centrality.

Figure 1. Degree centrality of node 1 is 1 and node 2, 3, 4, 5 is .25



Closeness Centrality: Ability to move information from one side of the network to another (i.e., gossip) is an important step towards establishing a shared perception of the worldwhether it has to do with someones choice of outfits at a party or the formation of a political movement.

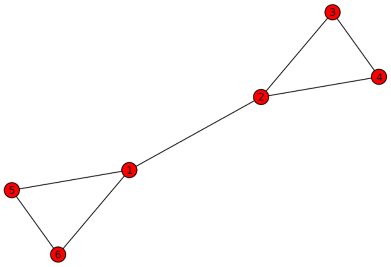
Thus, distance to others (or the inverse of it, closeness) can define a persons role in the network. This principle is at the root of the closeness centrality metricthe next centrality concept we will explore. The calculation of closeness centrality is computationally expensive: 1. Compute the shortest path between every pair of nodes using Dijkstras algorithm, and store these distances in a table. 2. For every node: a. Compute average distance to all other nodes b. Divide by maximum distance c. Closeness = 1 divided by average distance

Betweenness centrality: It is based on the assumption that an individual may gain power if he presides over a communication bottleneck. In terms of computer network it could be thought of as the node, that if removed would result in two disjoint network.

The way we measure betweenness is as follows; this algorithm is fairly time-consuming for large networks:

- Compute the shortest paths between every pair of nodes using Dijkstra's Algorithm.
- For every node I in the network: Count the number of shortest paths that I is on
- Normalize the numbers to bring your results to the 0-1 range.

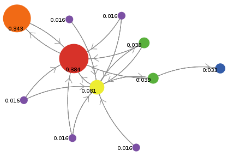
Figure 2. Betweenness Centrality of 1 and 2 is higher that 5,6,3 and 4 since more no of shortest path pass through 1 and 2.



Simplified PageRank algorithm

PageRank: is scaled between 0 and 1 and represents the likelihood that a person following links (i.e., traversing the network, surfing the web, etc) will arrive at a particular page or encounter a particular person. A 0.5 probability is commonly interpreted as a 50% chance of an event. Hence, a PageRank of 0.5 means there is a 50% chance that a person clicking on a random link will be directed to the document with the 0.5 PageRank.

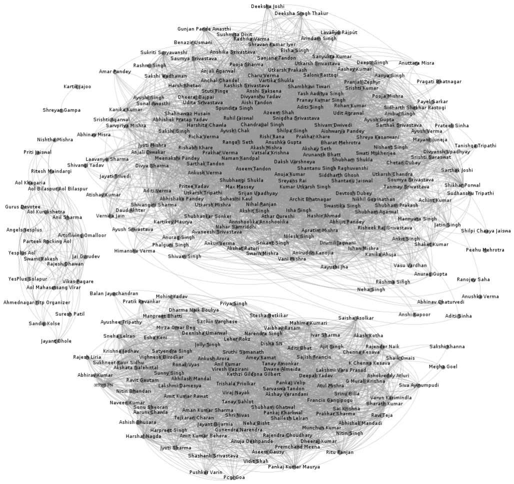
Figure 3. All the Nodes are assigned equal probability



Components and Subgraphs

- subgraph is a subset of the nodes of a network, and all of the edges linking these nodes. Any group of nodes can form a subgraphand further down we will describe several interesting ways to use this.
- Component subgraphs (or simply components) are portions of the network that are disconnected from each other. Before the meeting of Romeo and Juliet, the two families were quite separate (save for the conflict ties), and thus could be treated as components.

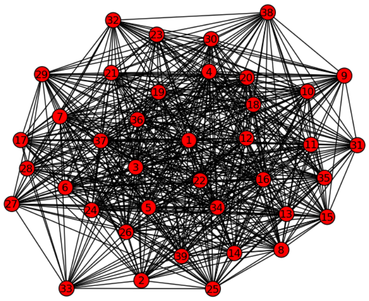
Figure 4. Facebook Network having 3 component



SubgraphsEgo Networks:Ego networks are sub-networks that are centered on a certain node. On Facebook and LinkedIn, these are simply described as your networkbut you can only access your own ego networks, and cant do a broader survey. Having a larger dataset allows us to survey and compare ego networks of various people.

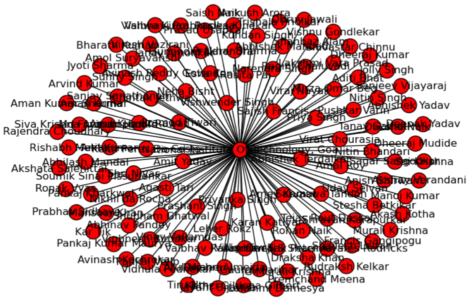
Cliques:While we might have an intuitive understanding of a clique in a social network as a cohesive group of people that are tightly connected to each other (and not tightly connected to people outside the group), in the field of SNA there is a formal mathematical definition that is quite a bit more rigorous. A clique is defined as a maximal complete subgraph of a given graphi.e., a group of people where everybody is connected directly to everyone else. The word maximal means that no other nodes can be added to the clique without making it less connected. Essentially, a clique consists of several overlapping closed triads, and inherits many of the culture-generating, and amplification properties of closed triads Multi Mode Network:Much of network data currently available comes in a 2-mode (or bimodal, or bipartite) formatthat is, there are two different types

Figure 5. Ego Graph of node 1 of radius 1



of nodes, and links determine relation- ships between one set of nodes and the other. In the the graph given below students are connected to college,which is a of different type. Such network are known as multi mode network since they contain two different type of entity connected together.

Figure 6. Multimode network of people connected to NIT, Goa in my Facebook network.



How are tools mentioned above used in Targeted Advertisement?: Graph api(Facebook n.d.) is used to extract data from facebook about friends general information. Using this information a knowledge graph connecting interest subject with people is created. Then People who are interested in topic are identified using the multi mode graph so constructed using simple edge connection identification. Then interest subject is removed so that the graph comprises entirely of people. Then sub component of the graphs are identified. Among these sub component people who are most influential are identified using centrality measure like degree, closeness , betweenness, page rank and HITS.

III. Real time information in disaster situation

Can we increase productivity of disaster recovery work by providing analyst real time information? If yes then by how much?Can we do it in all disaster scenario? Quick Availability of information in disaster struck situation can speed up disaster rescue effort. Time after the disaster is the most critical time since majority of life can be saved. Therefore the strategy employed is very essential. Information about Survivor Position, Volunteer Position, Operational Clinics, fuel station and road etc is very valuable in such scenario.

I have designed a simulation of the request sent to a server after disaster scenario. Consider a disaster situation, survivor can give his/her real time position information to server. These request would look like this:

- SURVIVOR me1 (386 169)
- SURVIVOR me2 (163 128)
- SURVIVOR me3 (158 48)
- SURVIVOR me4 (158 90)
- SURVIVOR me5 (84 309)
- SURVIVOR me6 (260 17)
- SURVIVOR me7 (387 393)
- SURVIVOR me8 (319 332)

In my simulation i have used python(Python n.d.) language for scripting and mongodb(MongoDB n.d.) for database. For graphical simulation Tkinter(Tkinter n.d.) library is used.

In this simulation humans are represented by class Person. Survivor are represented as Survivor class which inherits properties of a person. Volunteer also inherits from Person. Person has two attribute Name and Location. Location is stored as a Point object and Name is a string. The disaster struck area is abstracted as Cartesian field. In Field the survivor pops up with probability ppop. Volunteer pops with a probability one tenth of ppop. This makes the game interesting since the resources are constraint, therefore strategy of moving Volunteer must be optimal.

At each time step the field is updated and new survivor is added. These changes are made to database. Position of volunteer and presence of survivor is also tested to maintain consistency between database and program objects. Volunteer are redrawn at each time step to account for change in their position. Survivor are deleted based on the changes made to database and volunteer position.

Player uses another script to make changes to Volunteer position depending upon the amount of data available to him. There are two modes of game-play:

- No information about survivor position is available to player.
- Survivor position can be queried according to certain function.

This play simulates the actual work done by Palantir(Palantir n.d.*a*) Organization after Sandy Hurricane in NewYork, USA. Analytical tools were developed at runtime to suit the need. Network was established to connect volunteer with survivor.

PALANTIRS SOLUTION(Palantir n.d.*b*):Palantir sent several engineers to camp out at Team Rubicons command center in the Rockaways. There, they partnered with team leaders to develop an application that enabled volunteers to enter requests for assistance into Palantir Gotham through web-enabled mobile devices. Within days, volunteers on the ground were using iPads and smart phones to file requests for water, medical supplies, and home repairs in Palantir Gotham, where they were aggregated and analyzed as part of Team Rubicons broader operation. Volunteers also used the mobile devices to capture photos of flooded spaces, damaged buildings, and blocked roads, which were entered into Palantir Gotham as media objects and used to inform response planning. Analysts at Team Rubicons command center used Palantir Gotham to maintain situational awareness across all response activities. Coordinators tracked volunteer progress and dispatched additional support as needed. Analysts at Team Rubicons command center also used Palantir to connect to data sources provided by other organizations, including information on fuel availability, power grids, and available medical clinics. Volunteers on the ground accessed this information using Palantir and relayed the information to affected individuals. Using Palantir Gothams Map application, dispatchers could see where volunteers were located in relation to damaged houses

IV. Freakonomics

Can You answer any of these?

- Why should suicide bomber buy life insurance
- Is altruism real?
- Is Global Warming over hyped?
- Whats common between school teacher and sumo wrestler?
- Why are expert so often wrong?
- How much parent matter in success of child?
- Why do Drug Dealer Live with their mom?

Knowing what to measure and how to measure it helps in uncovering the hidden side of everything. Conventional wisdom is not always right.This means that decision based on our institution(which are formed by conventional wisdom) can get us into trouble. This is where data comes in. Through out the book Freakonomics(Stephen J. Dubner 2005) Hypothesis is tested against data. This has helped in validating some hypothesis while scraping others.

Economics at its core is study of incentives. Incentives are powerful bullet that can change situations. Consider the case of day care center in Haifa, Israel where bunch of economist conducted a study on incentives. Workers at center had to wait for parents who came late. In order to curb this they kept a fee of 3. Result? More no of parents started coming late!. This is where decision on conventional wisdom can back fire. Lets see why Decision on conventional wisdom was wrong, and how it could have been avoided. Incentives are classified into three categories:

- Moral:The reason why parents avoided coming late was of moral incentives
- Economic:Heavy tax on liquor is an Economic incentive.
- Social: Prostitute hide their profession of Social incentives

No of parents that came late increased because new fine gave economic incentive and reduced moral incentive.

All of the above will yield wrong answer if one uses his intuitions to answer them. These question require data against which hypothesis can be tested.

Since Steven D.Levitt(Author of Freakonomics) is an American Author, all his study were based in US. But the essence of the book was universal ie:

Conventional Wisdom is most often wrong! People respond to incentive Things can have distant and subtle cause

Freakonomics study has huge implication in policy formulation by government. Consider the case of Food Security bill that was passed recently, though it has noble intention, its not economically sound. Major problem in Food distribution system still remain unaddressed. If policy implication aren't tested and launched through out the country, it would create corruption and further aggravate the problem. Such kind of policy can have unintended consequences.

V. Text Analytics

Can a computer predict reaction to a youtube video just by accessing comment?Can we categorize article?

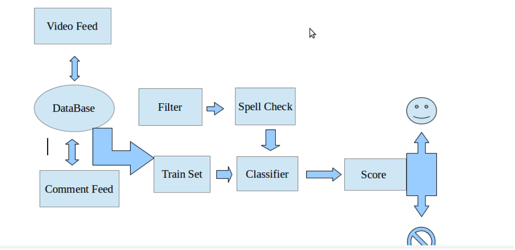
Natural Language Processing(Steven Bird and Loper n.d.) is one of the most challenging tasks in analytics since it involves machine learning,Algorithm, and deep understanding of theory of computation. Text analytics is widely deployed in sentiment analysis of newspaper article in stock prediction, user feedback to advertisement on social media sites, calculating productivity in office using mail analytics, advertisement and many more places. Lets start with a case study of youtube comment analyzer that I worked on over my summer internship at Innoplexus,Pune. Why Do Opinion Matters? Youtube video comments are very good indicator of the video. It helps us gauge peoples reaction to the video.

Peoples opinion about the video matters to advertising department of companies. This helps them evaluate the effectiveness of their investment. Tv Ads comes to youtube before going live(in most cases),therefore advertiser could gauge peoples reaction prior to launching ad in TV.

How Can We Gauge Opinion?To keep it simple we use + and approach to opinion classification. By classifying a comment as either positive or negative, we can get a percentage score of positive comment for a video, which is a good estimate of how mass feels about the advertisement.

Whats your approach?We use machine learning to classify comments. Using training set we train the classifier. As a filtering tool we use tf idf delta score instead of passing on the entire text. This is how it works!

Figure 7. Mining opinion and Sentiment analysis block diagram



How Do We get Data from youtube?Using gdata-python-api(Scudder n.d.) we extract data from youtube. This can be installed using source file.The feed we get is in xml format. Alternatively we can get data is json format by using urllib.urlopen function. Feed that we get is in json format and could be easily inserted in data. There is a minor glitch in inserting the feed directly to mongo db ie ’ćould not be at the start of the key. Therefore we replaced it with ’s’ in entire string.This inserts feed to youtube database and videos collection. Classifier:Naive Bayes classifier assigns a probability score to individual class. It assigns conditional probability to each class for a feature. This decides the likelihood of the class for a particular entry. In this example sports, automotive and murder mystery are classes and dark and football are feature. This way feature help decide class. Feature determines the accuracy of a class. Therefore choice of feature is central to text mining process. Video feed api returns 50 video entry in one request, whereas Comment Feed api returns 25 comments. A maximum of 1000 videos and comment could be retrieved. Search could be modified by changing url, for specification you can have a look at gdata reference. In most of the cases there aren’t 1000 comments for a video, therefore comment feed doesn’t contain entry key in it. This can be evaluated by studying the feed in python interactive shell. Based on this internal makeup the mosa feed collector were written. Feature accuracy result of my analysis over train set was

Figure 8. Naive Bayes Classifier

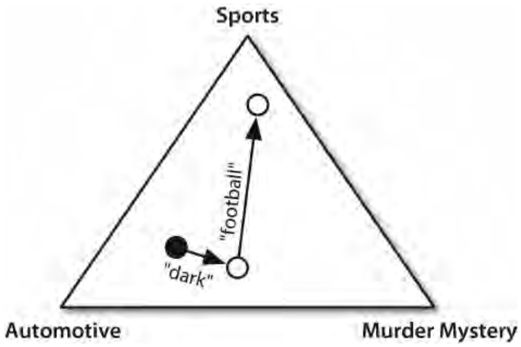


Table 1—Table caption

Feature	Percentage Accuracy
Polarity$_s core(using5pointscale)$	65
Polarity$_s core(using2pointscale)$	63
Term Presence	64
Term Presence(len(word)¿4)	70
Term Presence(len(word)¿5)	67
Term Presence(len(word)¿6)	6
Term Presence(len(word)¿7)	67
Term Presence(len(word)¿8)	65
Term Frequency(len(word)¿6)	68
Term Frequency(len(word)¿7)	66
Bigram	67
Tf-Idf-Delta	74

VI. Conclusion

Think Statistically!(Kahenman n.d.)Intuition can lead to disaster in personal and professional life. Decision that are based on data are empowered by tried and tested methods. One doesnt need to be a computer scientist or economist to analyze data. There are many open source tool available in market that automate decision making process. For computer scientist the quest is to come up with faster and memory efficient tools for data analysis. For economist quest is to come up with effiecient tools to improve our understanding of world around us. For developers, implementation of ideas into workable solution is quest. Lets make our life smarted by inclucating data based decision making. Hope you had fun reading it.

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