KE5205 TEXT MINING 2017

INTRODUCTION TO TEXT ANALYTICS
TOOLS & SOLUTIONS FOR TEXT ANALYTICS

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Objectives of this module

At the end of this module, you can:

- **Describe the difference between data mining and text mining**
- **List the 5 basic use cases for text mining and provide examples relevant to real business usage**

Outline for these modules

- **Setting the stage**
- **What is text mining?**
- **What can text mining do?**
  - The 5 Basic Use Cases of text mining
- **Tools & solutions for text mining**
- **Workshop Assessment & Discussion**

WHAT IS TEXT MINING

Exercise

What is Data Mining?

What is Data Mining?

the process of

- From Wikipedia:
  - The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use.
  - The actual data mining task is the automatic or semi-automatic analysis of large quantities of data to extract previously unknown interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection) and dependencies (association rule mining)

What is Data Mining?

the outcome of

- From a business perspective:
  - Data mining is the transformation of structured **data** into **answers** to **business questions**
    - If you don't have a business context…
      - Then data mining is an academic exercise
    - If you don't have a business question…
      - Then data mining is a waste of time
    - If you don't have data…
      - Then data mining is really easy, but really useless

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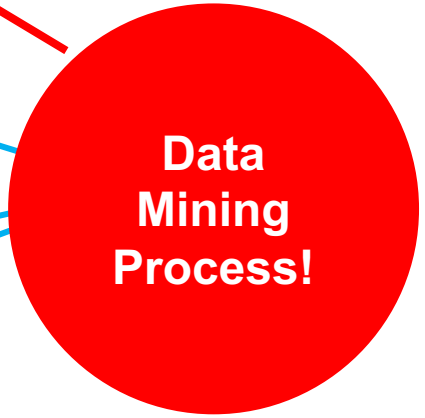

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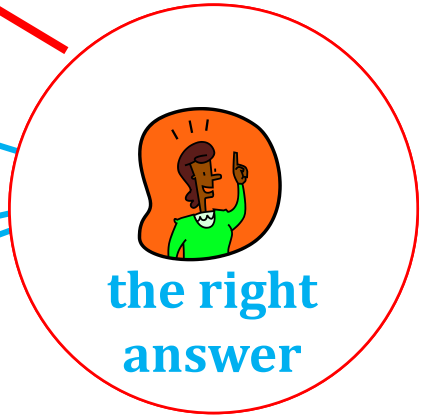


Easy Exercise

What is the Outcome of Text Mining?

What is the Outcome of Text Mining?

- Obvious answer?
  - Text mining is the task of transforming **unstructured text data** into answers to business questions

So, what is Text Mining?

- **What do you learn in "text mining"?**
  - Text mining is the task of transforming unstructured text data into structured numerical data so that automatic algorithms can be applied to large document databases
  - Converting text to numbers requires the use of techniques for handling text at the individual word/character level to semi-structured documents to unstructured documents to document databases

Unstructured to structured

Cust ID	Date:time	Model	Comments
00010	20121203: 2201	8560	Doesn't work – may have dropped. Out of warranty. Sent to svc.
00023	20121203: 1034	8850	Cannot roam. System is enabled. Reset settings on phone. Done.
00025	20121203: 1640	2338	No sound. Rebooted many times. Sent to svc. 3 months old.
01003	20121203: 1030	6000-1	Bought 2 weeks back. Gift. No receipt. Wants to upgrade. Sent to svc.
20456	20121203: 1025	6000-1	Out of space. 4GB uSD. Set default save to uSD for songs. Done.

Cust ID	Date:time	Model	Svc	Closed	Issue	. . . etc
00010	201212 03:2201	8560	1	1	99	
00023	201212 03:1034	8850	0	1	45	
00025	201212 03:1640	2338	1	1	12	
01003	201212 03:1030	6000-1	1	1	99	
20456	201212 03:1025	6000-1	0	1	28	

Text Mining converts unstructured text fields into one or more columns of easily processed numeric data

Why is text mining so tough?

- Feature extraction is necessary (and not easy!)
  - Need background knowledge and resources
- Documents represented by very many features
  - Short fat databases
  - Features that are significant may not be intuitive
- Patterns supported by small number of documents can be significant
- Very large numbers of patterns
  - Which patterns are significant in what context and domain?
  - Training data with outcomes to prune patterns
  - Interactive exploration also useful

WHAT CAN TEXT MINING DO?

THE 5 BASIC USE CASES OF TEXT MINING

Why text mining?

- **Data mining works**
  - Most information in the world is not in structured data form
  - The information in text needs to be unlocked
- Text is being created in digital format and available
  - Formal documents: word processing
  - Semi-structured text documents: patents, websites, …
  - Informal text: email, social media, sms, tweets, …
- Analyzing text, by itself or in conjunction with data, provides better outcomes for business decisions

From: http://www.youtube.com/watch?v=sTDWJBebwNY

What can text mining do?

5 basic Use Cases:

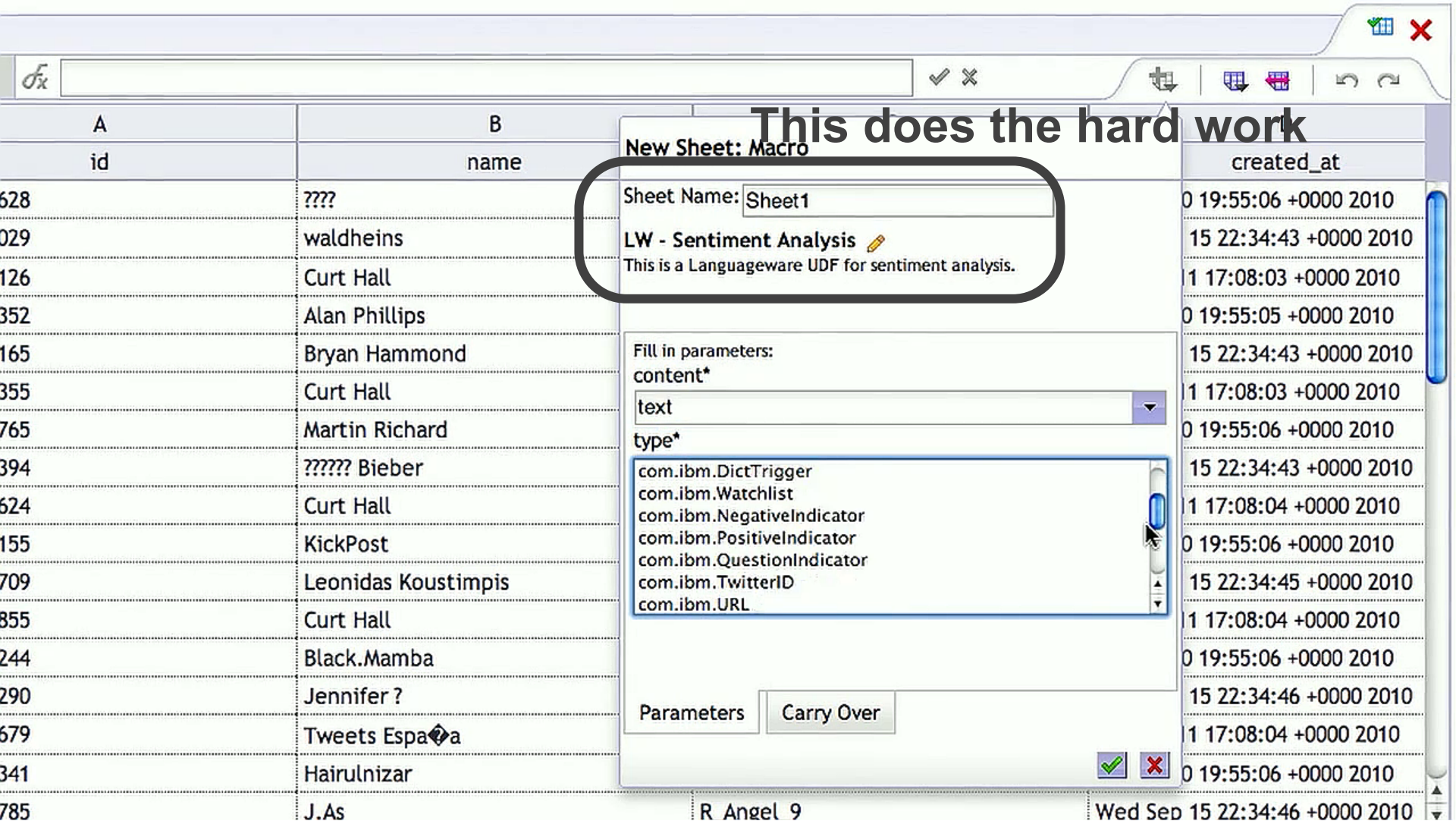
1. Extract “meaning” from unstructured text
2. Automatically put text into categories
3. Improve accuracy in predictive modeling or unsupervised learning
4. Identify specific or similar/relevant documents
5. Extract specific information from the text

1. Extract “meaning” from unstructured text

- **Extract answers from large corpus of small documents or small corpus or large documents that is not doable by human eye**
- **Sentiment analysis**
  - What are my customers saying about me?
  - What are the areas of concern to a target group?
  - Analyzing open-ended responses to survey questions
- **Trending themes in a stream of text**
  - Insurance claims trends, warranty claims analysis
- **Summarizing text**
  - Gisting – main theme of text documents/websites
  - Automatic keyword extraction

From: http://www.youtube.com/watch?v=PSq7hZ0shLs

Things to Note



Things to Note

Result Data: Ready

	type	name	screen_name	
1	com.ibm.en.PositiveIndicator	Special	Marlen1929	@m
2	com.ibm.en.PositiveIndicator	fantastic	Curtsiphone	Mak
3	com.ibm.en.PositiveIndicator	glorious	sharding	@Ke
4	com.ibm.en.PositiveIndicator	Amazing	thaibisz	Top
5	com.ibm.en.PositiveIndicator	like	MagsJB	My
6	com.ibm.en.PositiveIndicator	Cool	Cellphonez	Iph
7	com.ibm.en.PositiveIndicator	best	THE_Efram	@HI
8	com.ibm.en.PositiveIndicator	Quick	Leesa19043	@ilc
9	com.ibm.en.PositiveIndicator	First	paladigarisbiz	(HO
10	com.ibm.en.PositiveIndicator	wow	sjbuchanan007	@Ar
11	com.ibm.en.PositiveIndicator	Fast	Leesa19043	@ilc
12	com.ibm.en.PositiveIndicator	great	grattonboy	I'm
13	com.ibm.en.NegativeIndicator	doubt	gadgetinn	App
14	com.ibm.en.NegativeIndicator	hurt	msluvmylife	Girl
15	com.ibm.en.PositiveIndicator	like	POSTMODERNISM_	Rec
16	com.ibm.en.PositiveIndicator	like	gadgetinn	App

Decides sentiment based on lists of built-in keywords

What was the Business Context?

What was the Business Question/Need?

What was the data that was used?

What was the answer that was obtained?

What advantage did text mining provide in this case?

Exercise

2. Automatically put text into categories

- **Classification – assigning one or more predefined categories to a text document, for subsequent processing**
- **Automatic actions based on category**
  - Email routing, spam filtering
  - News filtering
- **Identifying anomalies based on text descriptions**
  - Fraud detection, normally flag for human intervention

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Text Mining Series - Automatically Classify Text Documents

StatSoft · 102 videos

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Uploaded on 27 Oct 2011

In this case study, there is a need to automatically classify text documents based on their content. Currently, the text articles are manually read and acted upon. Our goal is to automate as much as possible with a predictive model sorting the text files. Articles related to financial earnings should be flagged for review and sent to the appropriate individuals. In this video, we explore how STATISTICA Text Miner can be used to explore and index the text.

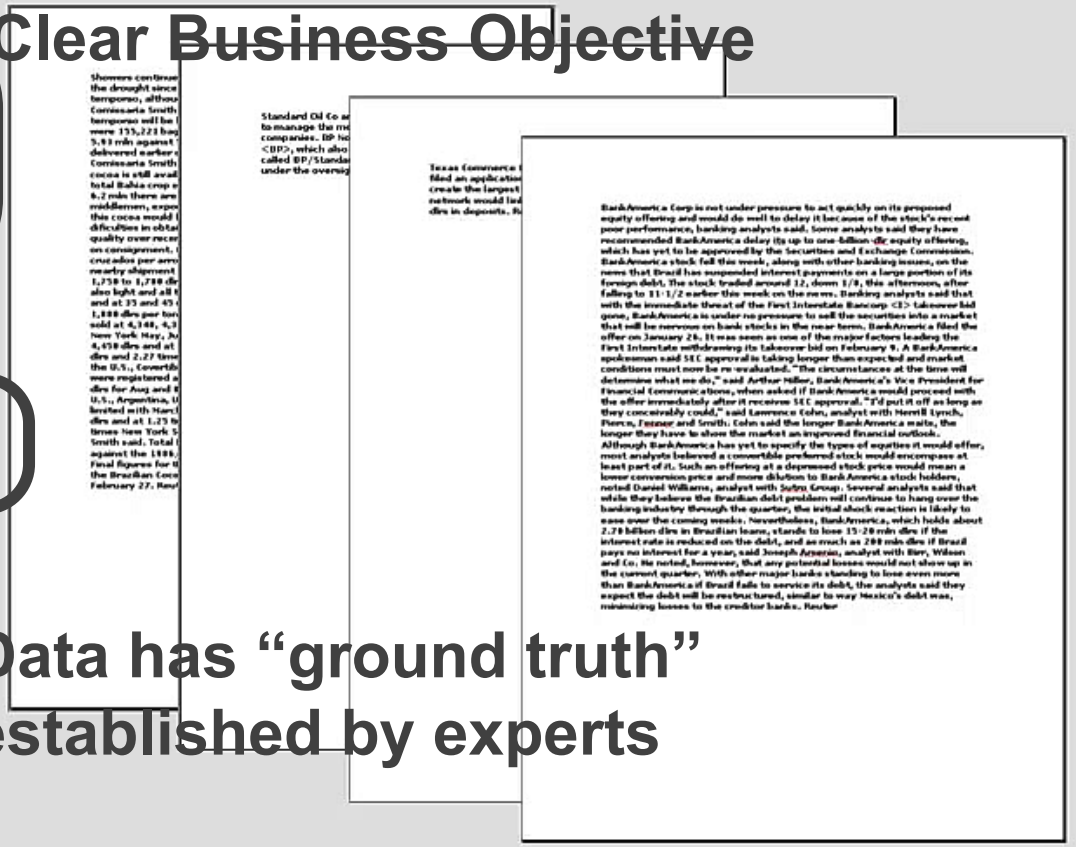
From: http://www.youtube.com/watch?v=Q5K3gyQJkC0

Things to Note

Predicting Article Subject Matter

- Project Goal
  - To automatically classify articles as either related to financial earning or not
- Project Plan
  - Using 5,000 expertly classified articles from Reuter, index the text and build predictive models that will classify new articles

Clear Business Objective



Data has "ground truth" established by experts

What was the Business Context?

What was the Business Question/Need?

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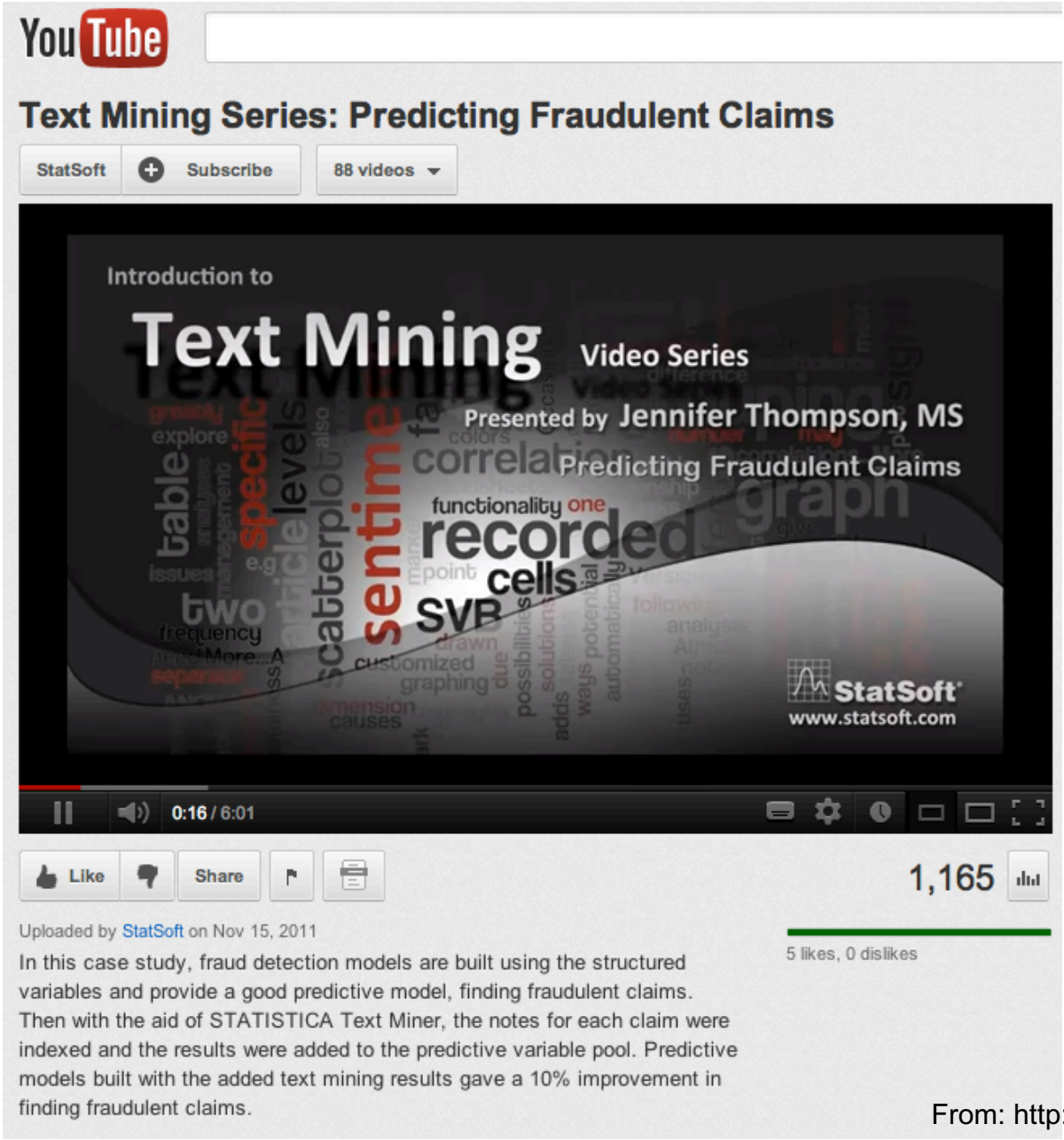
Exercise

3. Improve predictive accuracy in predictive modeling or unsupervised learning

- **Use text mining to improve data mining results ("Lift")**
- **Changing text to numbers to work with data mining**
  - Build a data matrix based on word/phrase counts
  - Compute various indices based on those matrices
  - Merge indices, counts with structured data for mining
- **Predicting insurance fraud from claims processing notes**
- **Using dictionaries to control vocabulary, reduce variance**

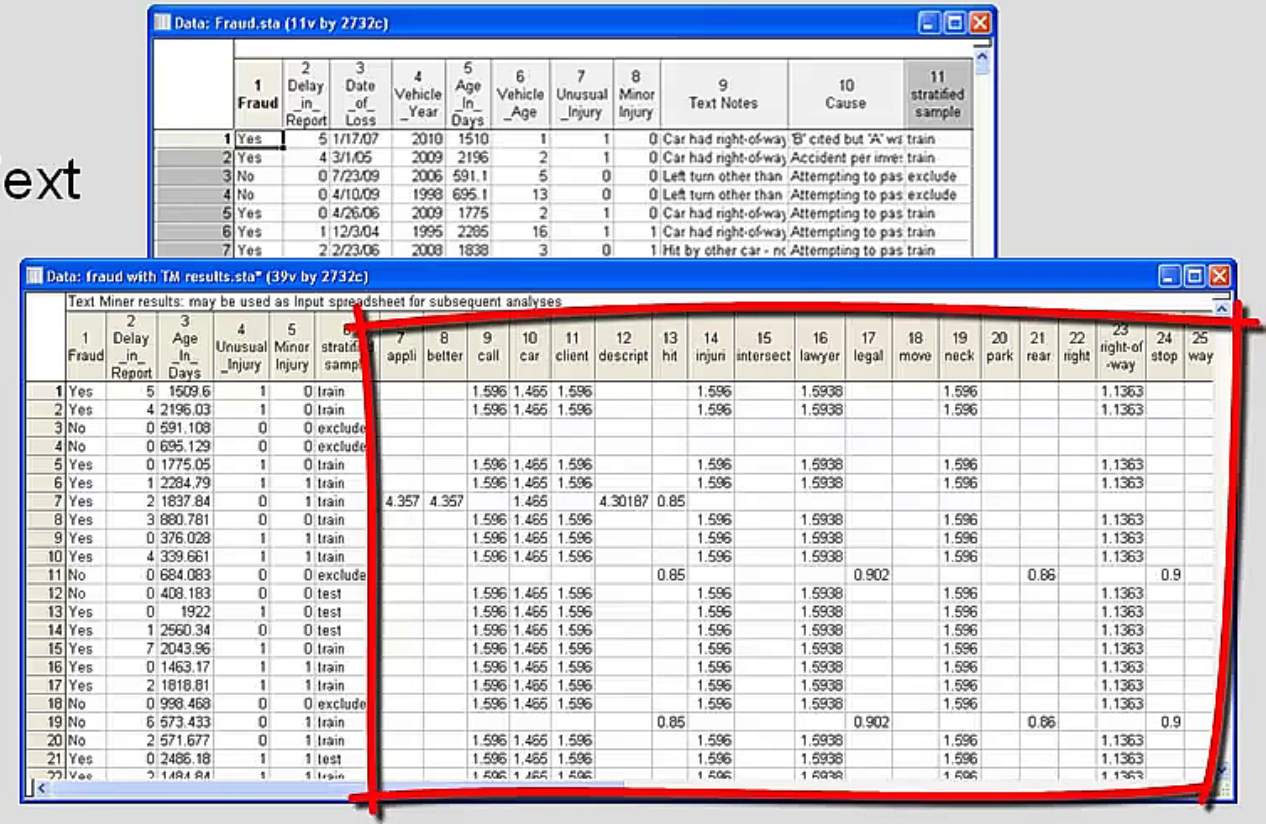


From: http://www.youtube.com/watch?v=OIQpm8qTog4

Things to Note

Predicting Fraudulent Claims

- Can predictability of fraudulent claims be improved by adding Text Mining results?
- Variables for analysis include
  - Delay in report
  - Policy age
  - Unusual injury
  - Minor injury
  - Text notes



Data: Fraud.sta (11v by 2732c)

	1 Fraud	2 Delay_in_Report	3 Date_of_Loss	4 Vehicle_Year	5 Age_In_Days	6 Vehicle_Age	7 Unusual_Injury	8 Minor Injury	9 Text Notes	10 Cause	11 stratified sample
1	Yes	5	1/17/07	2010	1510	1	1	0	Car had right-of-way	"B" cited but "A" wa	train
2	Yes	4	3/1/05	2009	2196	2	1	0	Car had right-of-way	Accident per inves	train
3	No	0	7/23/09	2006	591.1	5	0	0	Left turn other than	Attempting to pas	exclude
4	No	0	4/10/09	1998	695.1	13	0	0	Left turn other than	Attempting to pas	exclude
5	Yes	0	4/26/06	2009	1775	2	1	0	Car had right-of-way	Attempting to pas	train
6	Yes	1	12/3/04	1995	2285	16	1	1	Car had right-of-way	Attempting to pas	train
7	Yes	2	2/23/06	2008	1838	3	0	1	Hit by other car - no	Attempting to pas	train

Data: fraud with TM results.sta* (39v by 2732c)

Text Miner results: may be used as Input spreadsheet for subsequent analyses

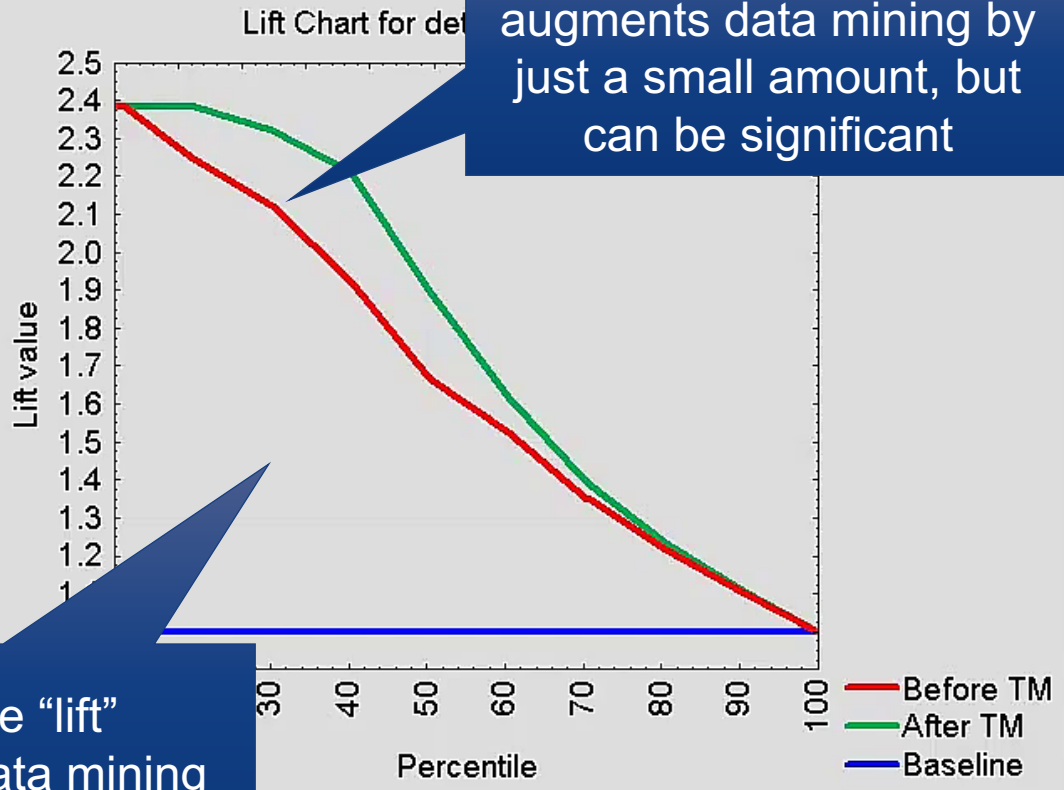
	1 Fraud	2 Delay_in_Report	3 Age_In_Days	4 Unusual_Injury	5 Minor Injury	6 stratified sample	7 appli	8 better	9 call	10 car	11 client	12 descript	13 hit	14 injuri	15 intersect	16 lawyer	17 legal	18 move	19 neck	20 park	21 rear	22 right	23 right-of-way	24 stop	25 way
1	Yes	5	1509.6	1	0	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
2	Yes	4	2196.03	1	0	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
3	No	0	591.108	0	0	exclude																			
4	No	0	695.129	0	0	exclude																			
5	Yes	0	1775.05	1	0	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
6	Yes	1	2284.79	1	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
7	Yes	2	1837.84	0	1	train	4.357	4.357		1.465		4.30187	0.85												
8	Yes	3	880.781	0	0	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
9	Yes	0	376.028	1	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
10	Yes	4	339.661	1	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
11	No	0	684.083	0	0	exclude							0.85				0.902				0.86			0.9	
12	No	0	408.183	0	0	test			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
13	Yes	0	1922	1	0	test			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
14	Yes	1	2560.34	0	0	test			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
15	Yes	7	2043.96	1	0	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
16	Yes	0	1463.17	1	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
17	Yes	2	1818.81	1	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
18	No	0	998.468	0	0	exclude			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
19	No	6	573.433	0	1	train							0.85				0.902				0.86			0.9	
20	No	2	571.677	0	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
21	Yes	0	2486.18	1	1	test			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		
22	Yes	2	1484.84	1	1	train			1.596	1.465	1.596			1.596		1.5938			1.596				1.1363		

Text converted into numbers

Things to Note

Predicting Fraudulent Claims – Project Steps

1. Build predictive models using the structured data
2. Index the text notes for accident claims
3. Build predictive models using the structured data and text mining results
4. Compare model performance



Text mining normally augments data mining by just a small amount, but can be significant

Most of the "lift" provided by data mining on structured data

What was the Business Context?

What was the Business Question/Need?

What was the data that was used?

What was the answer that was obtained?

What advantage did text mining provide in this case?

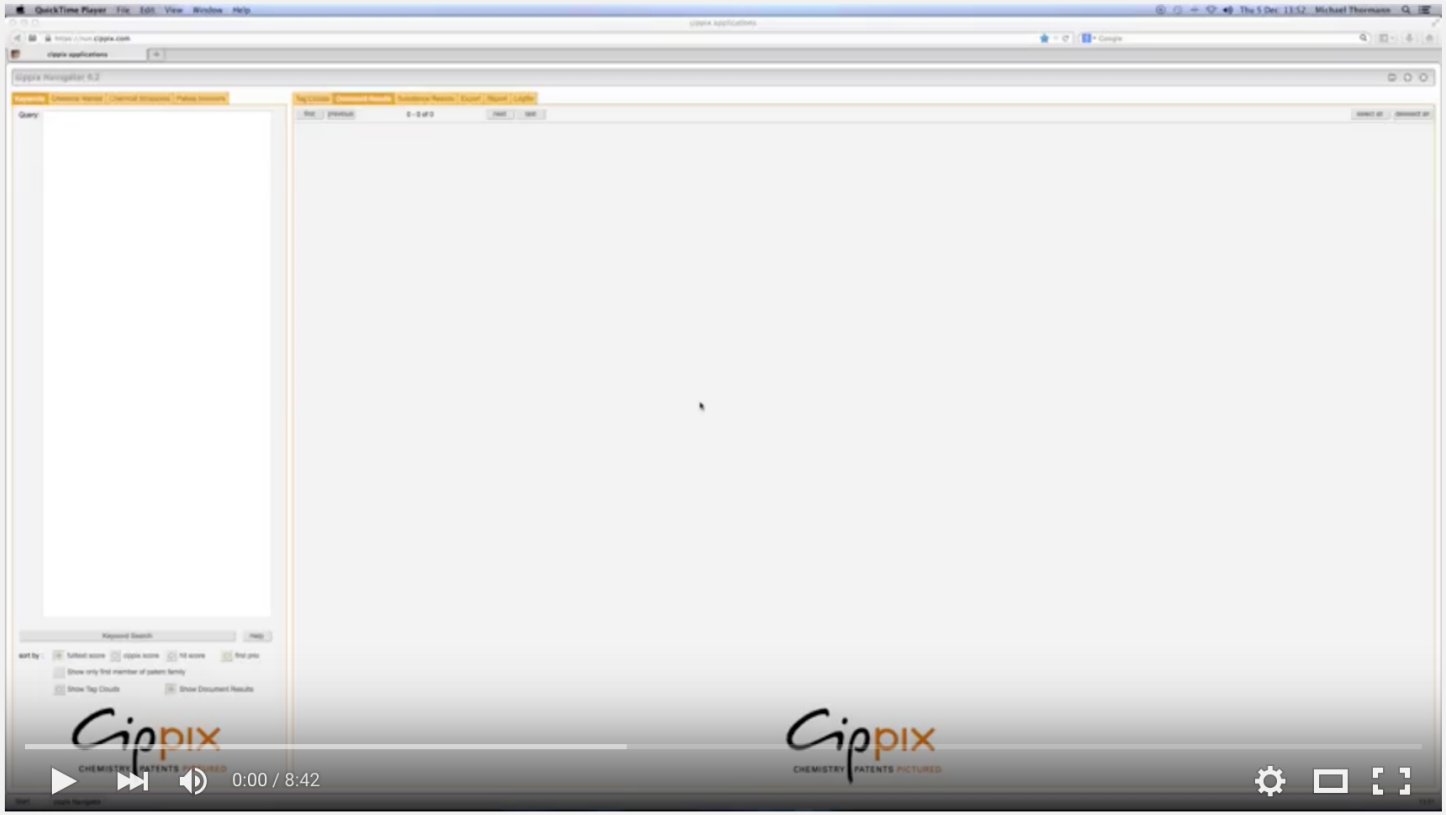
Exercise

4. Identify specific or similar/relevant documents

- **Document searching** – given a specific documents, identify other documents in the corpus which are similar and relevant
- Create a pool of similar/linked documents for analysis
  - Patent search, primary research
  - Forensic investigations into text
- Web search

YouTube

cippix tutorial



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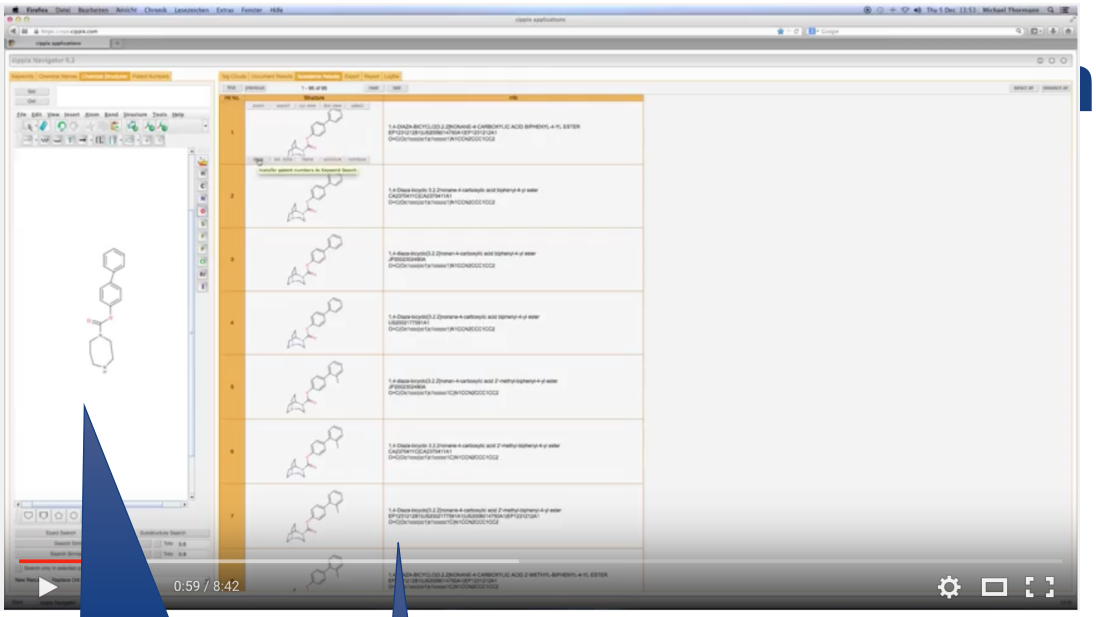
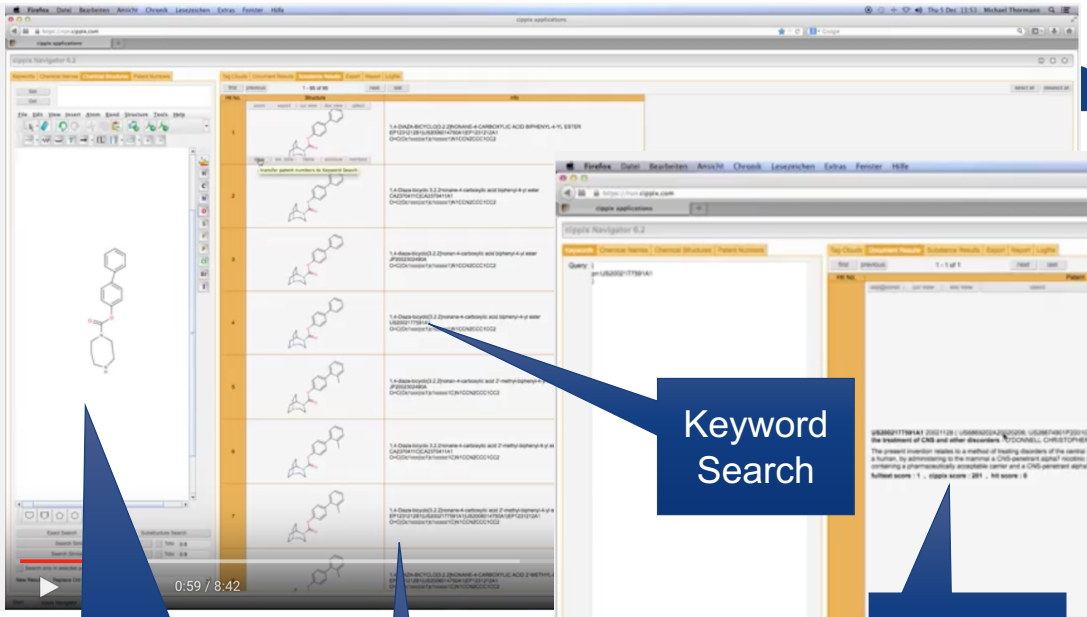
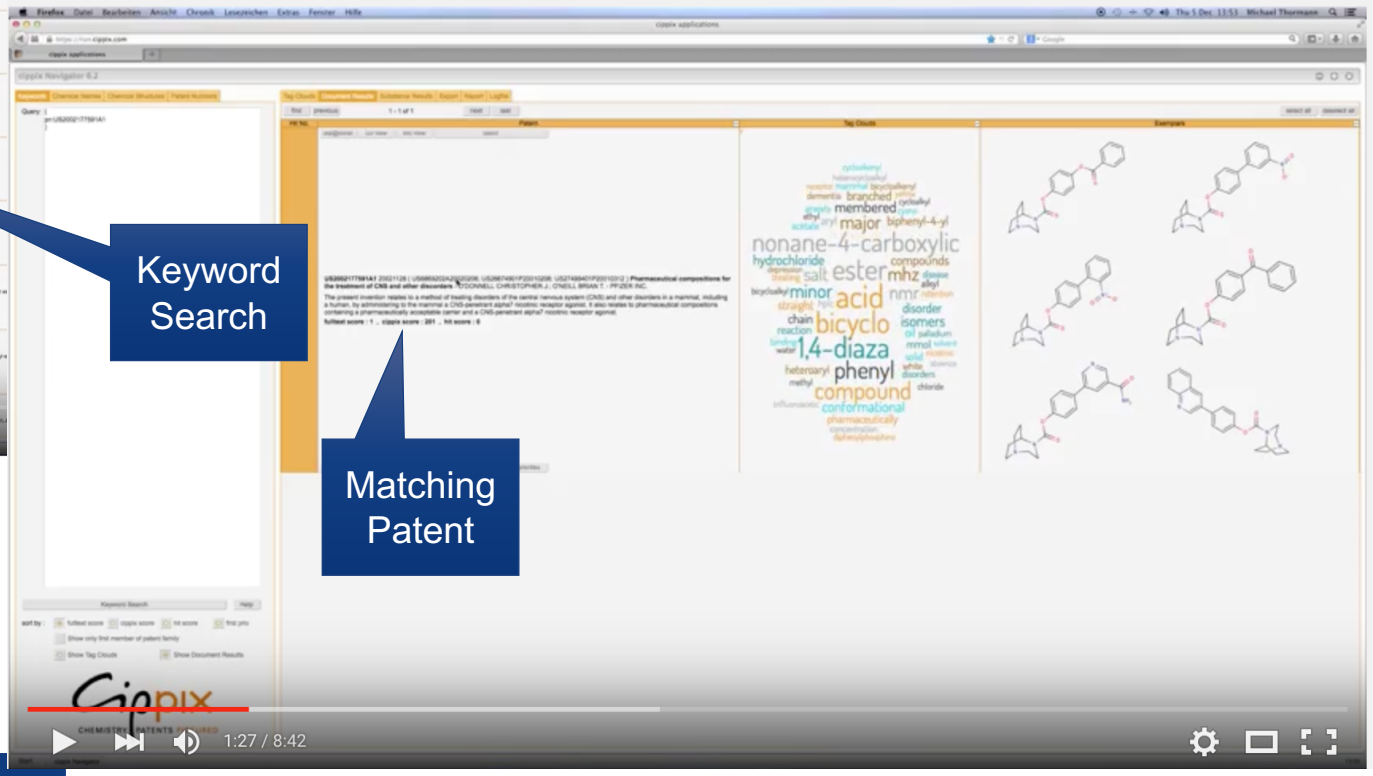


Chemical Substructure query

Matching Documents

hings to Note





Keyword Search

Matching Patent

Chemical Substructure query

Matching Documents

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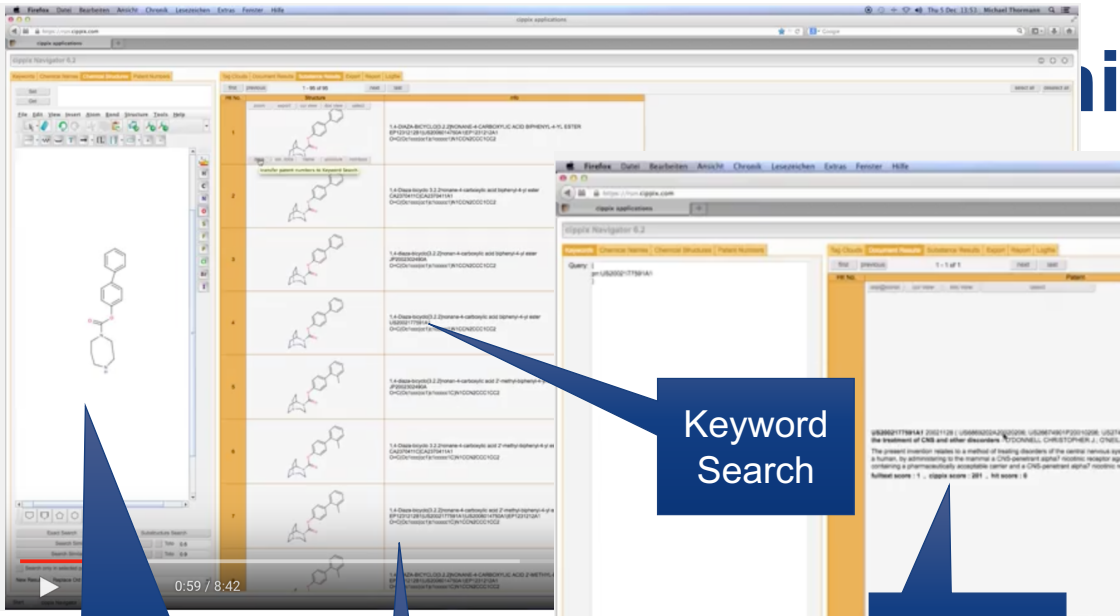

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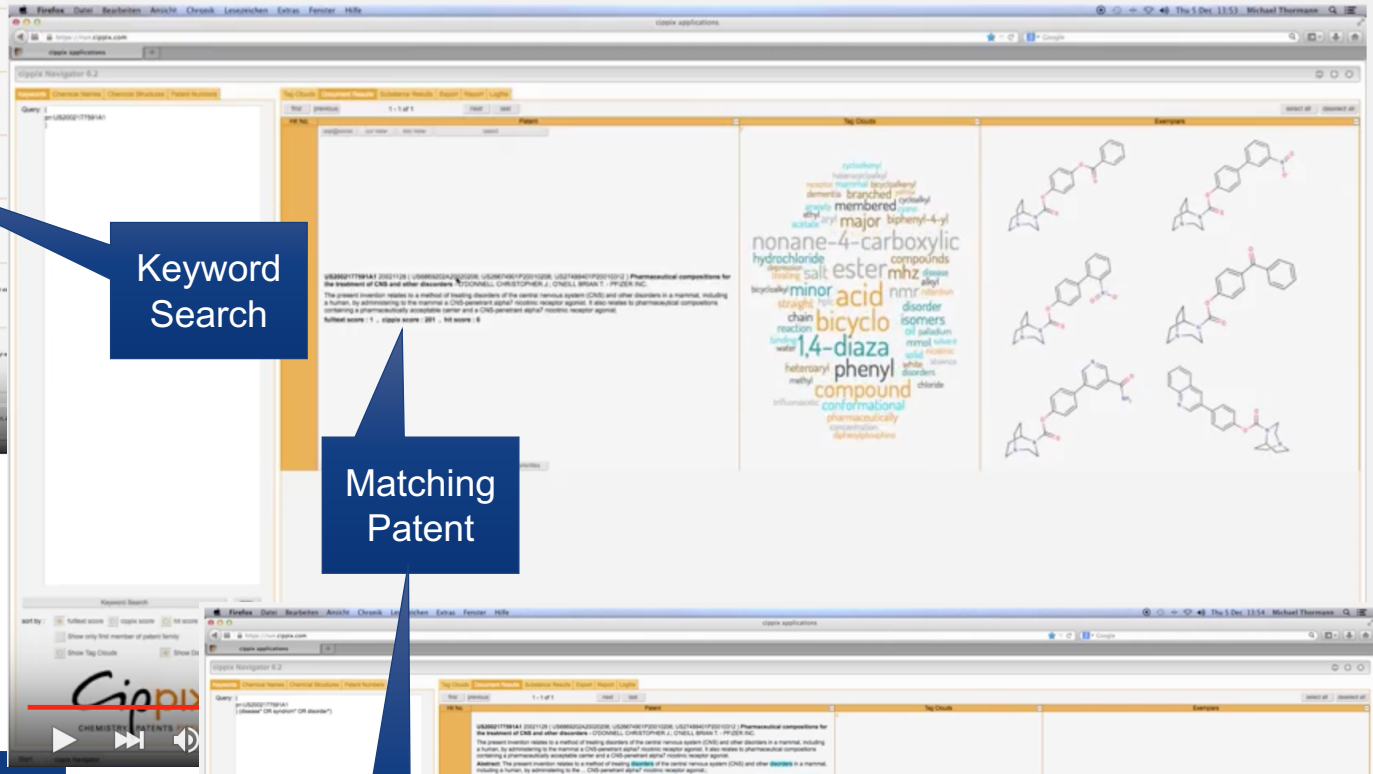
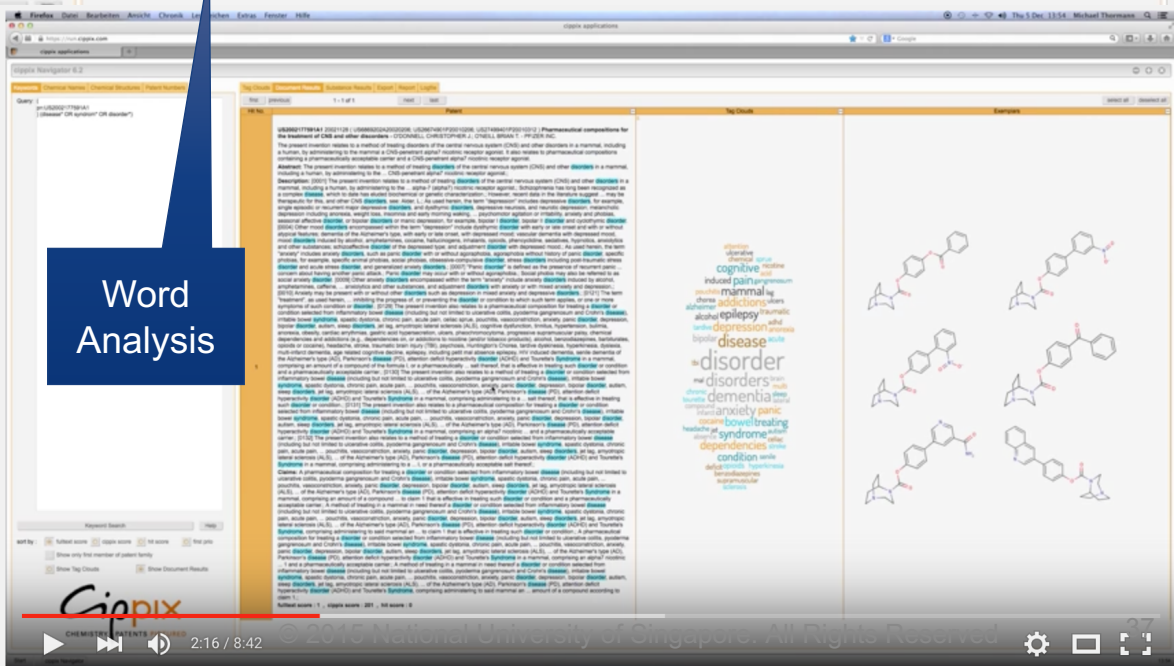


Chemical Substructure query

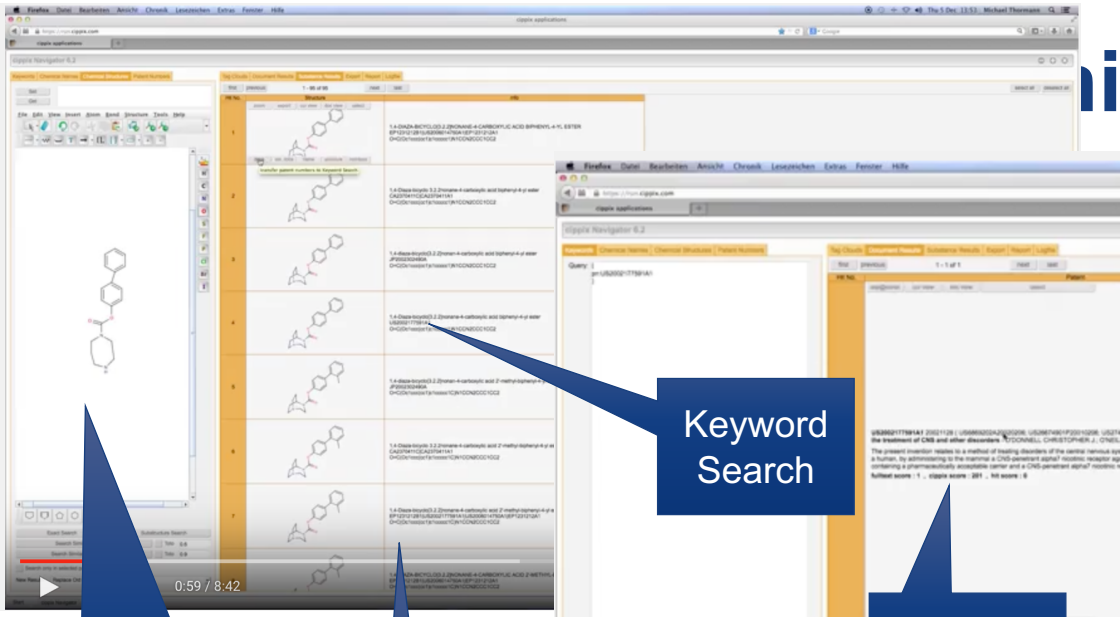
Matching Patent

Matching Documents



Word Analysis

hings to Note



Keyword Search

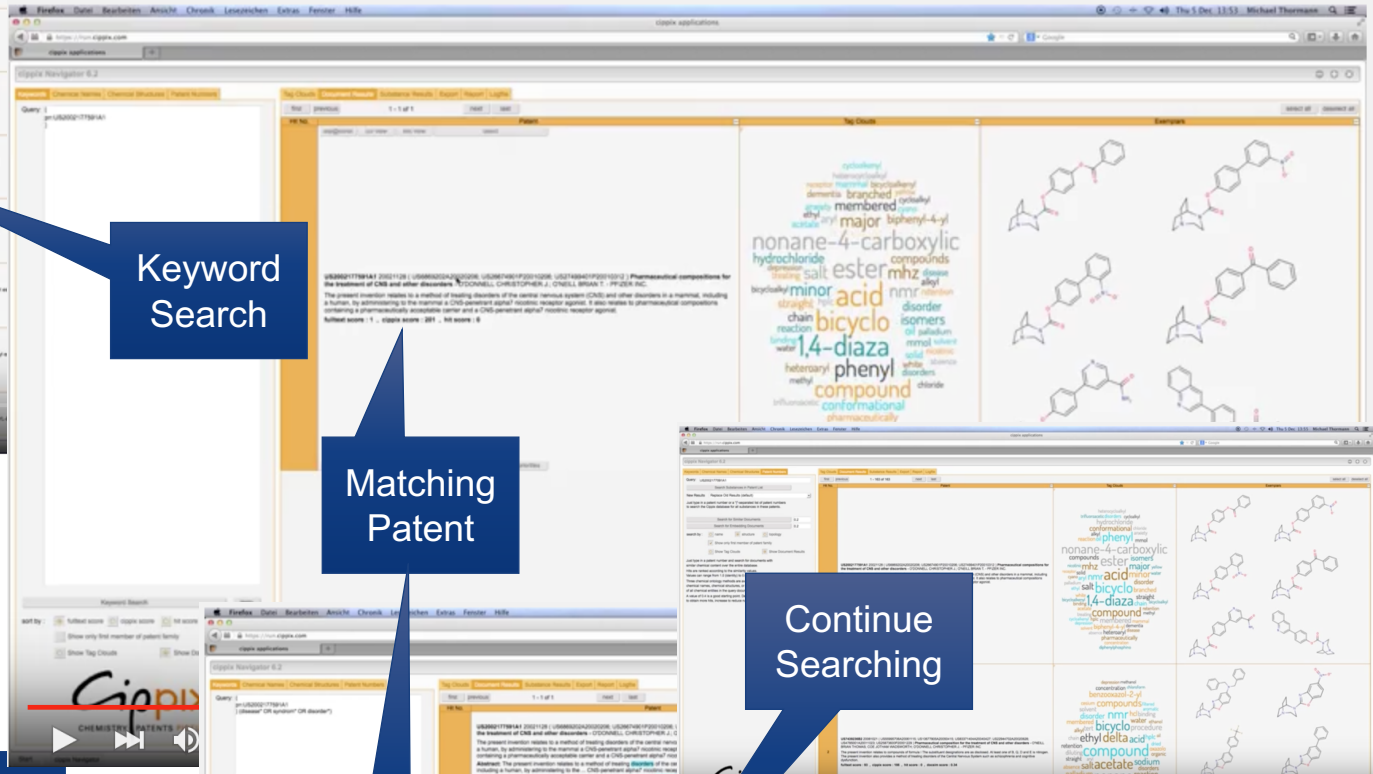
Chemical Substructure query

Matching Documents

Matching Patent

Word Analysis

Continue Searching



What was the Business Context?

What was the Business Question/Need?

What was the data that was used?

What was the answer that was obtained?

What advantage did text mining provide in this case?

Exercise

5. Extract specific information from the text

- **There are many answers in text documents. The problem is given a question, how to get the answer, not just the document. The task is called "question answering" (QA)**
- **At a more basic level, identify and extract "named entities" from documents and corpora**
- **Automatic QA**
  - Compare interest rates at banks for best deal
  - Automated help desk and FAQs
- **Name Entity Extraction (NER)**
  - Dates, money sums, organizations, stock symbols, etc.

YouTube

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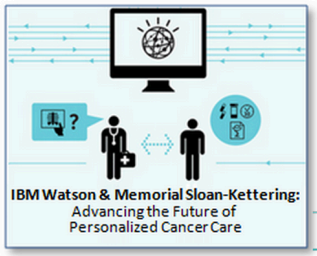
High Tech Advancing Future of Personalized Cancer Care

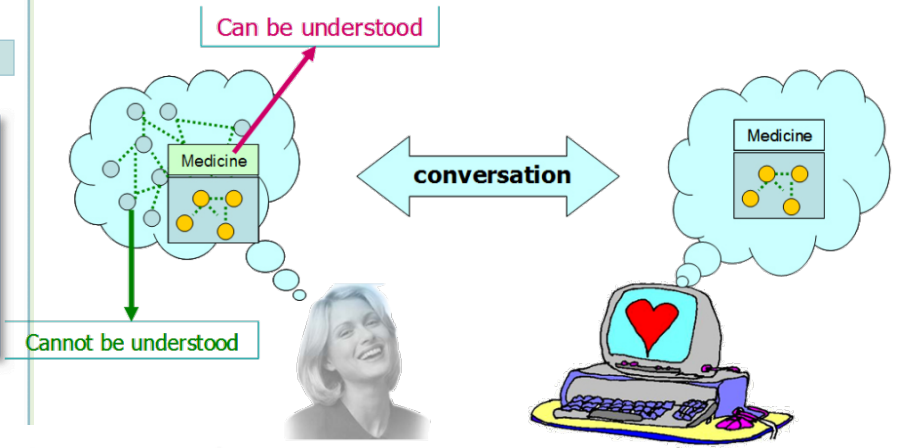
01/19/2013

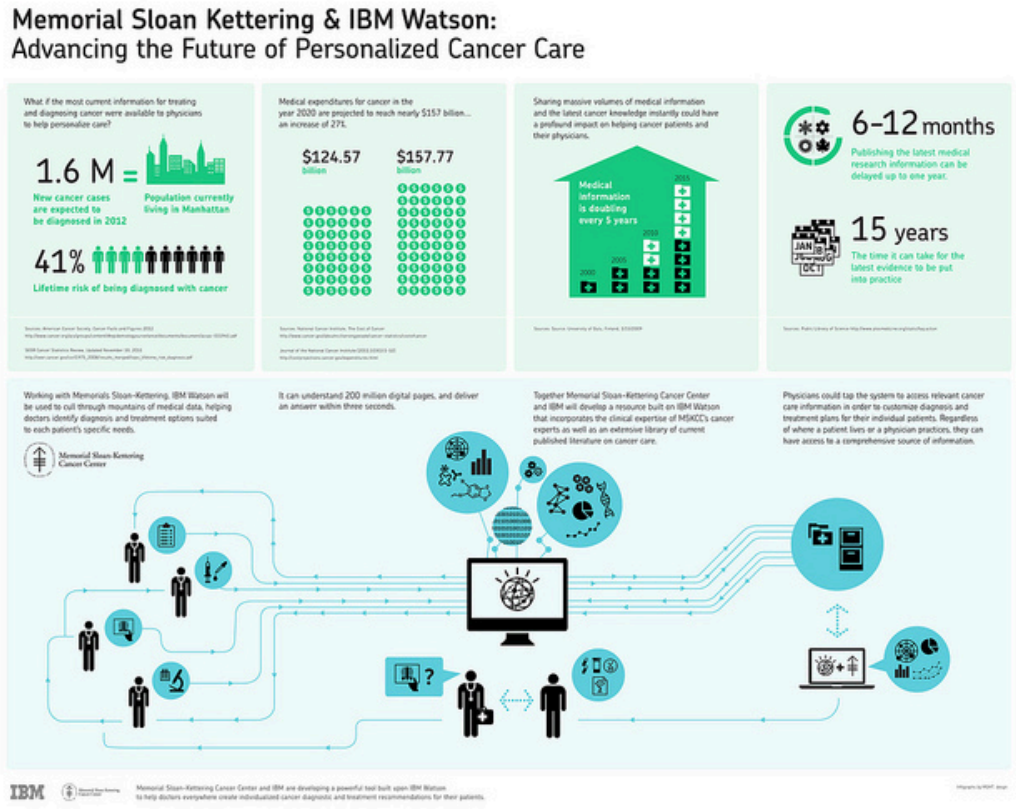
Memorial Sloan-Kettering Cancer Center, IBM to Collaborate in Applying Watson Technology to Help Oncologists

IBM Watson combined with MSKCC's clinical knowledge will help physicians access and integrate latest science and knowledge



New York City – 22 Mar 2012: Memorial Sloan-Kettering Cancer Center and IBM have agreed to collaborate on the development of a powerful tool built upon IBM Watson in order to provide medical professionals with improved access to current and comprehensive cancer data and practices. The resulting decision support tool will help doctors everywhere create individualized cancer diagnostic and treatment recommendations for their patients based on current evidence.





YouTube IBM Watson Demo/ Oncology Diagnosis and Treatment

IBM Watson Demo Oncology Diagnosis and Treatment 2 min.

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The IBM Watson Cancer Diagnosis and Treatment Adviser demo was created in close collaboration with Memorial Sloan Kettering, one of the world's preeminent cancer treatment and research institutions. The demo scenario follows the interactions of a hypothetical oncologist and patient as they move through consultations, tests, treatment options, patient preferences and pre-authorization. It showcases IBM Watson's

https://www.youtube.com/watch?v=T7M1Dgyaapw

What was the Business Context?

What was the Business Question/Need?

What was the data that was used?

What was the answer that was obtained?

What advantage did text mining provide in this case?

Exercise

TOOLS & SOLUTIONS FOR TEXT MINING

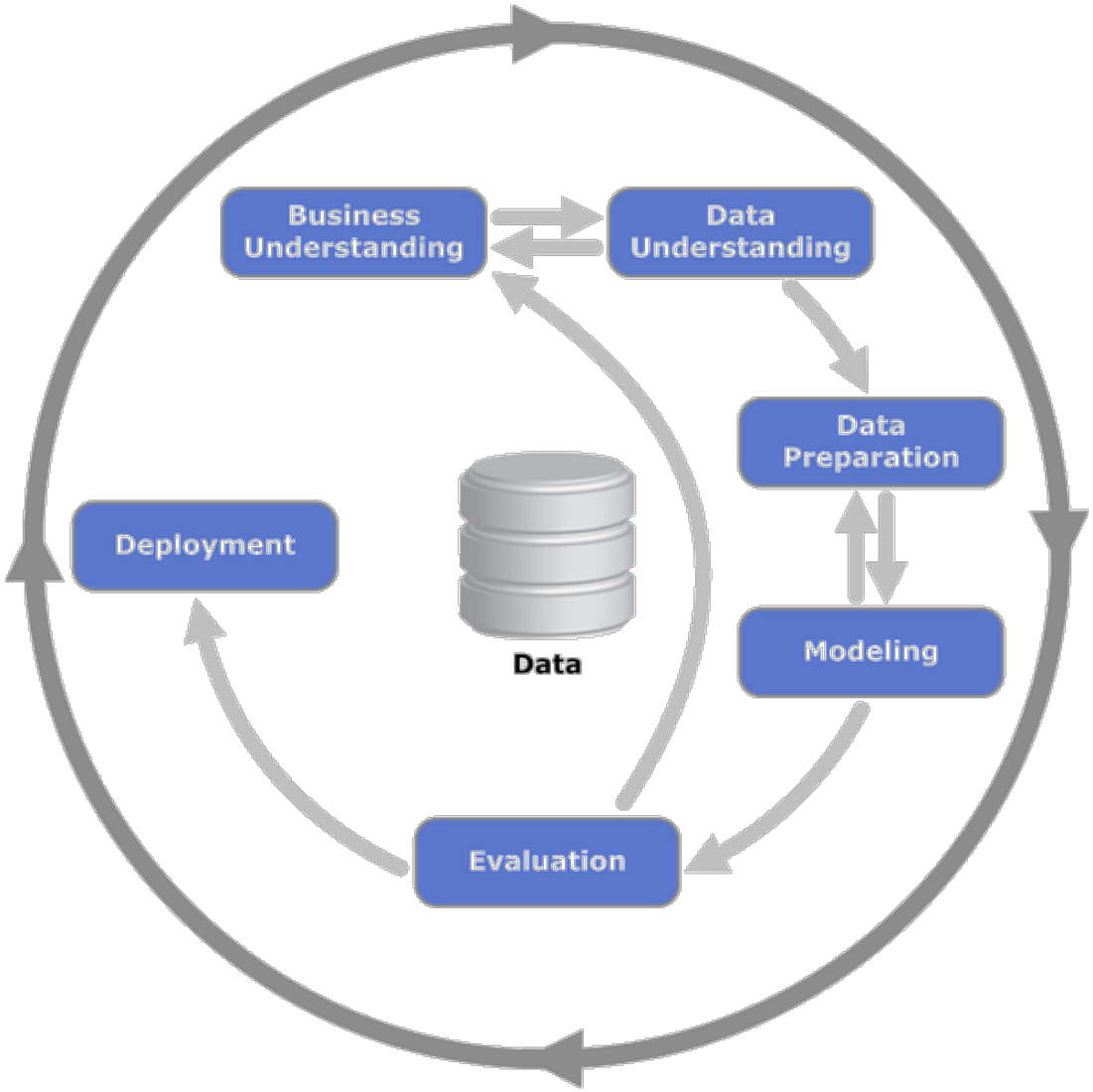
6 Phases of CRISP-DM
Cross-Industry Standard Process for Data Mining

- **Business Understanding**: This initial phase focuses on understanding the project objectives and requirements from a business perspective, and then converting this knowledge into a data mining problem definition, and a preliminary plan designed to achieve the objectives.
- **Data Understanding**: The data understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data, or to detect interesting subsets to form hypotheses for hidden information.
- **Data Preparation**: The data preparation phase covers all activities to construct the final dataset (data that will be fed into the modeling tool(s)) from the initial raw data. Data preparation tasks are likely to be performed multiple times, and not in any prescribed order. Tasks include table, record, and attribute selection as well as transformation and cleaning of data for modeling tools.
- **Modeling**: In this phase, various modeling techniques are selected and applied, and their parameters are calibrated to optimal values. Typically, there are several techniques for the same data mining problem type. Some techniques have specific requirements on the form of data. Therefore, stepping back to the data preparation phase is often needed.
- **Evaluation**: At this stage in the project you have built a model (or models) that appear to have high quality, from a data analysis perspective. Before proceeding to final deployment of the model, it is important to more thoroughly evaluate the model, and review the steps executed to construct the model, to be certain it properly achieves the business objectives. A key objective is to determine if there is some important business issue that has not been sufficiently considered. At the end of this phase, a decision on the use of the data mining results should be reached.
- **Deployment**: Creation of the model is generally not the end of the project. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized and presented in a way that the customer can use it. Depending on the requirements, the deployment phase can be as simple as generating a report or as complex as implementing a repeatable data mining process. In many cases it will be the customer, not the data analyst, who will carry out the deployment steps. However, even if the analyst will not carry out the deployment effort it is important for the customer to understand up front the actions which will need to be carried out in order to actually make use of the created models.

From: http://en.wikipedia.org/wiki/Cross_Industry_Standard_Process_for_Data_Mining

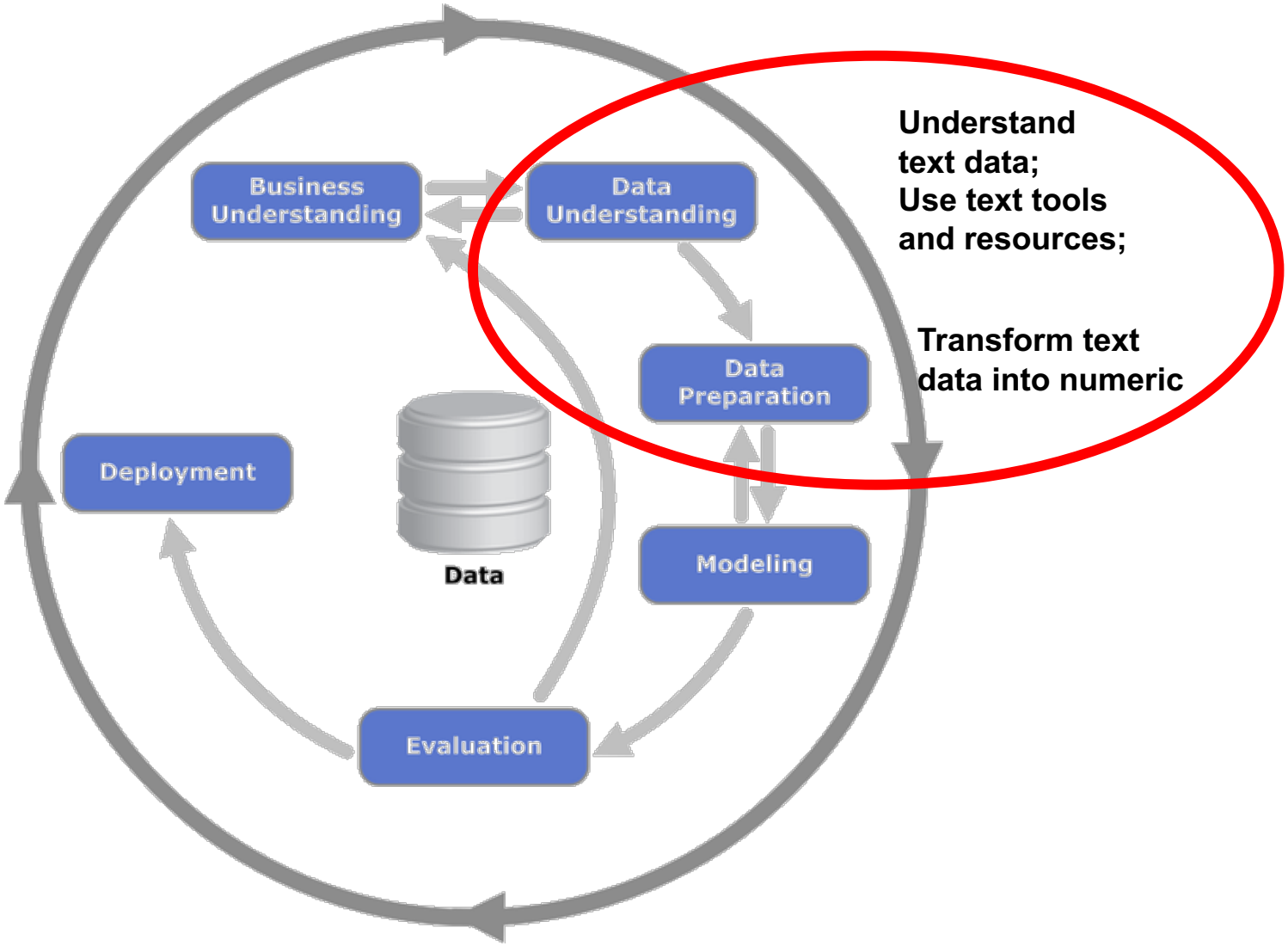
CRISP-DM Process Diagram

Note the Arrows – iteration & sequence



From: http://en.wikipedia.org/wiki/Cross_Industry_Standard_Process_for_Data_Mining

CRISP-DM Process with Text Mining

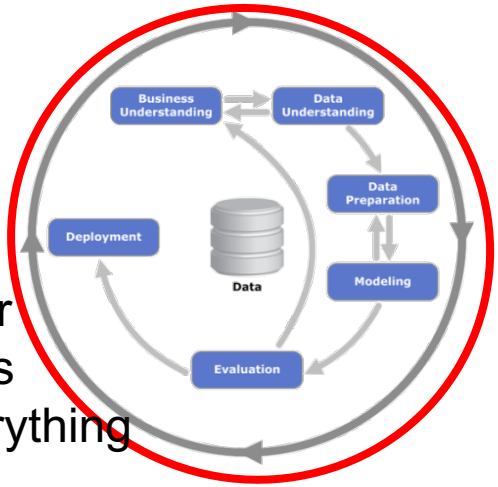


From: http://en.wikipedia.org/wiki/Cross_Industry_Standard_Process_for_Data_Mining

Factors to decide on the solution

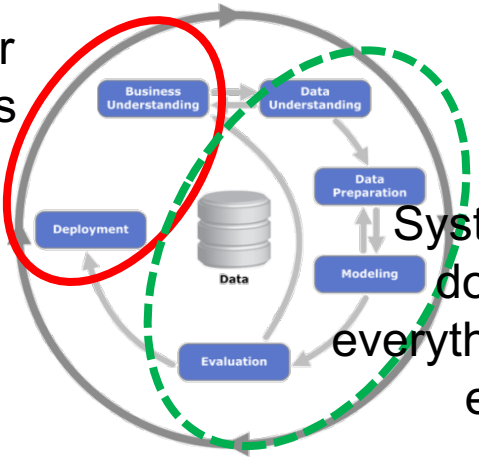
- **What are your business outcomes?**
  - Numbers? Or "Actionable Insights"
- **How much skill do you have?**
  - In the process, in the tool, in the linguistic ability
- **How much time do you have?**
  - Skill + time = capacity to improve the linguistic extraction models
  - No time OR no skill = stay with the defaults
- **How often are you going to do this?**
  - Ad hoc usage? Unique data?
  - Regular runs over similar data?
- **What's your budget?**

Some possible models…

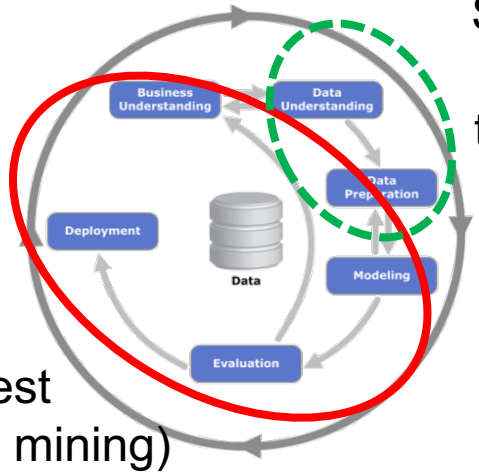


User does everything

User does this part



System does everything else



System does the text portion

User does the rest (data mining)

Factors to decide on the tool(s)

- **How general/flexible a tool do you want?**
  - Does one thing only (e.g., text survey) or very flexible?
  - Domain specific (dictionaries) or open domain?
  - Monolingual, true-multilingual, or translated multilingual?
- **How much help do you need?**
  - Open source tools are “free”, but you learn for yourself
  - Vendor tools are expensive, but you get training and support
  - Is the support local or overseas?
  - Courses can be tool specific, or tool independent
- **Do you need to do it yourself?**
  - If you know what you need, can you outsource the how?

Reflection

What is the Business of my organisation?

What is the Business Need?

Do we have data that can be used? Who understands it?

What answer do we want? What action will result from that?

Reference & Resources

- Chris Manning & Hinrich Schutze, ***Foundations of Statistical Natural Language Processing***, MIT Press, 1999
- NLP resources: http://nlp.stanford.edu/links/statnlp.html
- Christopher Potts (Stanford University), Sentiment Symposium Tutorial, http://sentiment.christopherpotts.net/index.html
- John Elder, Gary Miner, Bob Nisbet. ***Practical Text Mining and Statistical Analysis for non-Structured Text Data Applications***, Academic Press, 2012
- Roger Bilisoly. ***Practical Text Mining with PERL***, John Wiley & Sons, 2008