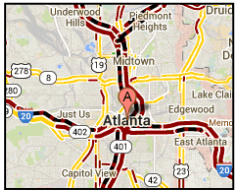
Data Science

Large-scale Data is Everywhere!

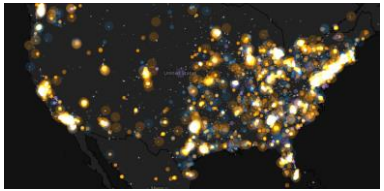
- There has been enormous data growth in both commercial and scientific databases due to advances in data generation and collection technologies
- New mantra
  - Gather whatever data you can whenever and wherever possible.
- Expectations
  - Gathered data will have value either for the purpose collected or for a purpose not envisioned.

Cyber Security

E-Commerce

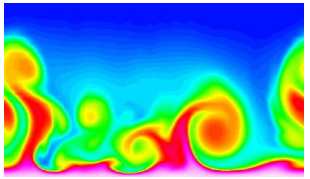


Traffic Patterns



Social Networking: Twitter

Sensor Networks



Computational Simulations

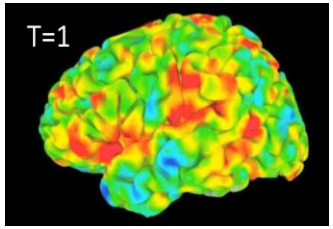
Why Data Science? Commercial Viewpoint

- Lots of data is being collected and warehoused
  - Web data
    - Google has Peta Bytes of web data
    - Facebook has billions of active users
  - purchases at department/ grocery stores, e-commerce
    - Amazon handles millions of visits/day
  - Bank/Credit Card transactions

- Computers have become cheaper and more powerful
- Competitive Pressure is Strong
  - Provide better, customized services for an edge (e.g. in Customer Relationship Management)

Why Data Science? Scientific Viewpoint

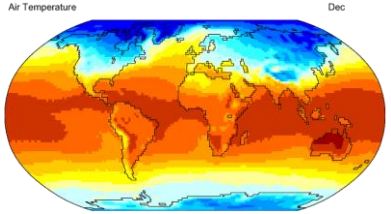
- Data collected and stored at enormous speeds
  - remote sensors on a satellite
    - NASA EOSDIS archives over petabytes of earth science data / year
  - telescopes scanning the skies
    - Sky survey data
  - High-throughput biological data
  - scientific simulations
    - terabytes of data generated in a few hours
- Data science helps scientists
  - in automated analysis of massive datasets
  - In hypothesis formation



fMRI Data from Brain

Sky Survey Data

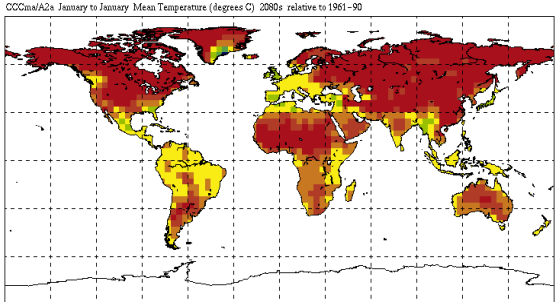
Gene Expression Data



Surface Temperature of Earth

Great Opportunities to Solve Society's Major Problems

Improving health care and reducing costs



Predicting the impact of climate change

Finding alternative/ green energy sources

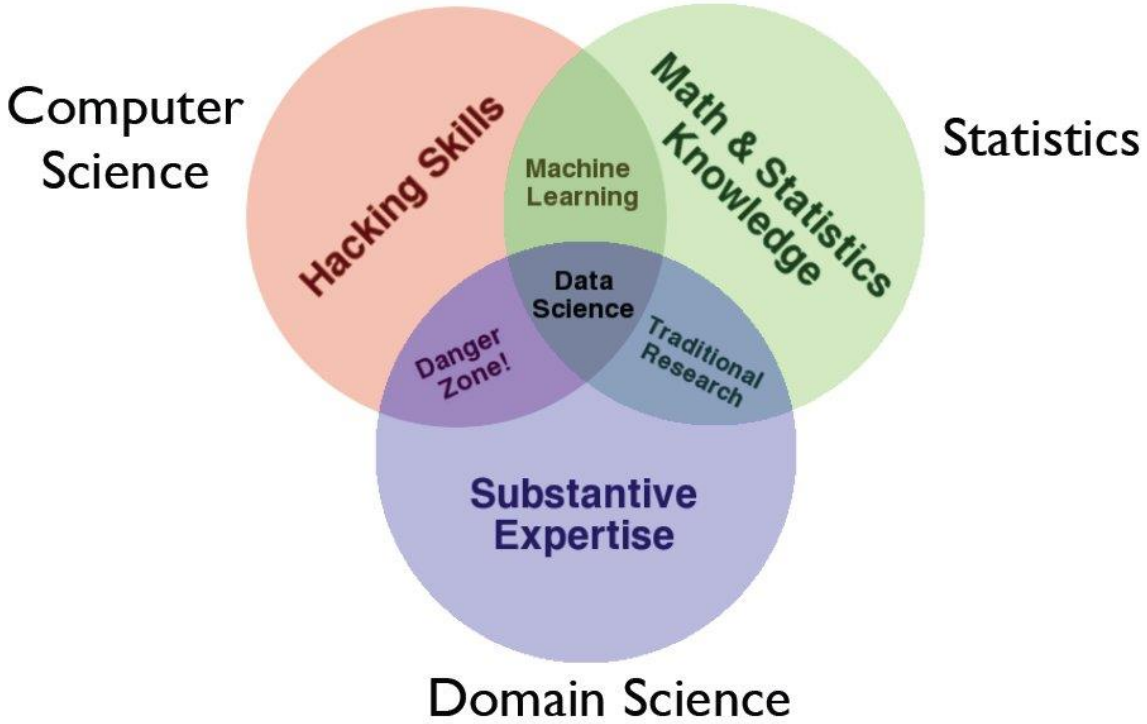
Reducing hunger and poverty by increasing agriculture production

What is Data Science?

Like any emerging field, it isn’t yet well defined, but incorporates elements of:

- Exploratory Data Analysis and Visualization
- Machine Learning and Statistics
- High-Performance Computing technologies for dealing with scale.

Skill Sets for Data Science



Appreciating Data

Computer Scientists do not naturally appreciate data: it's just stuff to run through a program.

The usual way to test algorithm performance is to run the implementation on "random data".

But interesting data sets are a scarce resource, which requires hard work and imagination to obtain.

Computer vs. Real Scientists (1)

- Scientists strive to understand the complicated and messy natural world, while computer scientists build their own clean and organized virtual worlds. Thus:
- Nothing is ever completely true or false in science, while everything is either true or false in Computer Science / Mathematics.

Computer vs. Real Scientists (2)

- Scientists are data-driven, while computer scientists are algorithm-driven.
- Scientists obsess about discovering things, which computer scientists invent rather than discover.
- Scientists are comfortable with the idea that data has errors; computer scientists are not.

Genius vs. Wisdom

Software developers are hired to produce code.

Data Scientists are hired to produce insights.

Genius shows in finding the right answer!!!

Wisdom shows in avoiding the wrong answers.

Data science (like most things) benefits more from wisdom than from genius.

Developing Wisdom

- Wisdom comes from experience.
- Wisdom comes from general knowledge.
- Wisdom comes from listening to others.
- Wisdom comes from humility, observing how often you have been wrong and why/how.

I seek pass on wisdom, through my experience on the difficulty of making good predictions.

Developing Curiosity

- The good data scientist develops a curiosity about the domain/application they are working in.
- They talk shop with the people whose data they are working on.
- They read the newspaper every day, to get a broader perspective on the world.

Asking Good Questions

Software developers are not encouraged to ask questions, but data scientists are:

- What exciting things might you be able to learn from a given data set?
- What things do you/your people really want to know?
- What data sets might get you there?

Let’s Practice Asking Questions!

Who, What, Where, When, and Why on the following datasets:

- Baseball-reference.com
- Google ngrams
- NYC taxi cab records

Baseball-Reference.com: biosketch

BASEBALL-REFERENCE.COM

S-R: M

play index | players | teams | seasons | managers | leaders | awards | postseason | boxes | japan | nlb | minors | draft

Mobile Site **You Are Here** > Home > Encyclopedia of Players > R Listing > **Babe Ruth Statistics and**

News: s-r blog:KBO Stats back to 1999 – Baseball-Reference.com

Babe Ruth Player Page » Batting | Pitching | Fielding | Minors | News Archive (1456) | Bullpen | Oracle

Babe Ruth

Like 1,213 people like this. +1 +25 Recommend this

George Herman Ruth (Babe, The Bambino or The Sultan Of Swat)

Positions: Outfielder and Pitcher
Bats: Left, **Throws:** Left
Height: 6' 2", **Weight:** 215 lb.

Born: February 6, 1895 in Baltimore, MD
High School: St. Mary's HS (Baltimore, MD) (All Transactions)
Debut: July 11, 1914 (Age 19.155)
Rookie Status: Exceeded rookie limits during 1915 season [*]
Teams (by GP): Yankees/RedSox/Braves 1914-1935

Final Game: May 30, 1935 (Age 40.113)
Inducted into the Hall of Fame by BBWAA as Player in 1936 (215/226 ballots). Induction ceremony in (
View **Babe Ruth Page** at the Baseball Hall of Fame (plaque, photos, videos).
Died: August 16, 1948 in New York, NY (Aged 53.192)
Buried: Gate of Heaven Cemetery, Hawthorne, NY
View Player Bio from the **SABR BioProject**
About biographical information

Transactions

July 9, 1914: Purchased with Ernie Shore and Ben Egan by the Boston Red Sox from Baltimore (International) for more than $25000. more than $25000
December 26, 1919: Purchased by the New York Yankees from the Boston Red Sox for $100,000.
February 26, 1935: Released by the New York Yankees.
February 26, 1935: Signed as a Free Agent with the Boston Braves.

The transaction information used here was obtained free of charge from and is copyrighted by RetroSheet. We attempt to update transactions throughout the season.

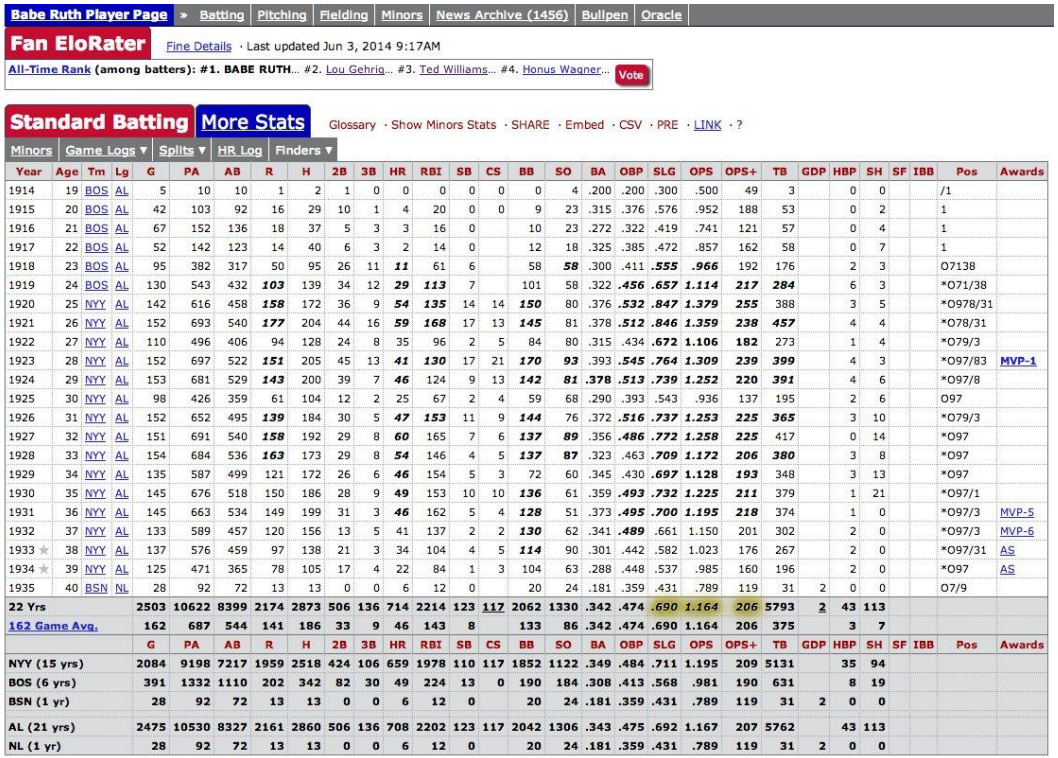
Salaries

Convert to YYYY $$'s Salaries may not be complete (especially pre-1985) and may not include some earned bonuses

Year	Age	Team	Salary	ServTm(OpnDay)	Sources	Notes/Other Sources
1914	19	Boston Red Sox	$2,500	?	Bill James Historical Abstract	Annualized rate; came up late in season
1915	20	Boston Red Sox	$3,500	?	Bill James Historical Abstract	
1916	21	Boston Red Sox	$3,500	?	Contract at HOF	
1917	22	Boston Red Sox	$3,500	?	Contract at HOF	BJHA: $5,000; Baseball Timeline $7,000
1918	23	Boston Red Sox	$9,000	?	Allan Wood, 1918, at 183	Includes $1,000 midseason raise, $1,000 WS bonus
1919	24	New York Yankees	$10,000*	?	Michael Haupert research of HOF contracts	Contract at HOF:10000.00,
1920	25	New York Yankees	$20,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:20000.00,
1921	26	New York Yankees	$20,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:30000.00,Plus $5K for '20 and '21 exhibitions, $50/HR (59)m
1922	27	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:52000.00,
1923	28	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:52000.00,
1924	29	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:52000.00,
1925	30	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:52000.00,
1926	31	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:52000.00,
1927	32	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	5/23/27 AL letter:70000.00,
1928	33	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	5/23/27 AL letter:70000.00,
1929	34	New York Yankees	$52,000*	?	Michael Haupert research of HOF contracts	5/23/27 AL letter:70000.00,
1930	35	New York Yankees	$70,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:80000.00,
1931	36	New York Yankees	$70,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:80000.00,
1932	37	New York Yankees	$70,000*	?	Michael Haupert research of HOF contracts	M. Smelser, Life That Ruth Built, p. 441:75000.00,Plus 25% of all exhibition-game profits
1933	38	New York Yankees	$80,000*	?	Michael Haupert research of HOF contracts	M. Smelser, Life That Ruth Built, p. 456:52000.00,Plus 25% of revenue from in-season exhibitions
1934	39	New York Yankees	$80,000*	?	Michael Haupert research of HOF contracts	1/16/36 TSN, per government report:36696.00,$35,000 salary plus 25% of exhibition profits
1935	40	New York Yankees	$75,000*	?	Michael Haupert research of HOF contracts	Bill James Historical Abstract:35000.00,Annualized rate; retired early in season
1936	41	New York Yankees	$52,000	?	Michael Haupert research of HOF contracts	
1937	42	New York Yankees	$35,000	?	Michael Haupert research of HOF contracts	
Career to date (may be incomplete)			$1,020,000			

Statistical Record of Play

Summary statistics of each years batting, pitching, and fielding record, with teams and awards.



Babe Ruth Player Page » Batting | Pitching | Fielding | Minors | News Archive (1456) | Bullpen | Oracle

Fan EloRater — Fine Details · Last updated Jun 3, 2014 9:17AM

All-Time Rank (among batters): #1. BABE RUTH... #2. Lou Gehrig... #3. Ted Williams... #4. Honus Wagner... Vote

Standard Batting | More Stats — Glossary · Show Minors Stats · SHARE · Embed · CSV · PRE · LINK · ?

Minors | Game Logs ▾ | Splits ▾ | HR Log | Finders ▾

Year	Age	Tm	Lg	G	PA	AB	R	H	2B	3B	HR	RBI	SB	CS	BB	SO	BA	OBP	SLG	OPS	OPS+	TB	GDP	HBP	SH	SF	IBB	Pos	Awards
1914	19	BOS	AL	5	10	10	1	2	1	0	0	0	0	0	0	4	.200	.200	.300	.500	49	3		0	0			/1	
1915	20	BOS	AL	42	103	92	16	29	10	1	4	20	0	0	9	23	.315	.376	.576	.952	188	53		0	2			1	
1916	21	BOS	AL	67	152	136	18	37	5	3	3	16	0		10	23	.272	.322	.419	.741	121	57		0	4			1	
1917	22	BOS	AL	52	142	123	14	40	6	3	2	14	0		12	18	.325	.385	.472	.857	162	58		0	7			1	
1918	23	BOS	AL	95	382	317	50	95	26	11	***11***	61	6		58	***58***	.300	.411	***.555***	***.966***	192	176		2	3			O7138	
1919	24	BOS	AL	130	543	432	***103***	139	34	12	***29***	***113***	7		101	58	.322	***.456***	***.657***	***1.114***	***217***	***284***		6	3			*O71/38	
1920	25	NYY	AL	142	616	458	***158***	172	36	9	***54***	***135***	14	14	***150***	80	.376	***.532***	***.847***	***1.379***	***255***	388		3	5			*O978/31	
1921	26	NYY	AL	152	693	540	***177***	204	44	16	***59***	***168***	17	13	***145***	81	.378	***.512***	***.846***	***1.359***	***238***	***457***		4	4			*O78/31	
1922	27	NYY	AL	110	496	406	94	128	24	8	35	96	2	5	84	80	.315	.434	***.672***	**1.106**	**182**	273		1	4			*O79/3	
1923	28	NYY	AL	152	697	522	***151***	205	45	13	***41***	***130***	17	21	***170***	***93***	.393	***.545***	***.764***	***1.309***	***239***	***399***		4	3			*O97/83	MVP-1
1924	29	NYY	AL	153	681	529	***143***	200	39	7	***46***	124	9	13	***142***	***81***	***.378***	***.513***	***.739***	***1.252***	***220***	***391***		4	6			*O97/8	
1925	30	NYY	AL	98	426	359	61	104	12	2	25	67	2	4	59	68	.290	.393	.543	.936	137	195		2	6			O97	
1926	31	NYY	AL	152	652	495	***139***	184	30	5	***47***	***153***	11	9	***144***	76	.372	***.516***	***.737***	***1.253***	***225***	***365***		3	10			*O79/3	
1927	32	NYY	AL	151	691	540	***158***	192	29	8	***60***	165	7	6	***137***	***89***	.356	***.486***	***.772***	***1.258***	***225***	417		0	14			*O97	
1928	33	NYY	AL	154	684	536	***163***	173	29	8	***54***	146	4	5	***137***	***87***	.323	.463	***.709***	***1.172***	***206***	***380***		3	8			*O97	
1929	34	NYY	AL	135	587	499	121	172	26	6	***46***	154	5	3	72	60	.345	.430	***.697***	**1.128**	***193***	348		3	13			*O97	
1930	35	NYY	AL	145	676	518	150	186	28	9	**49**	153	10	10	***136***	61	.359	***.493***	***.732***	***1.225***	***211***	379		1	21			*O97/1	
1931	36	NYY	AL	145	663	534	149	199	31	3	***46***	162	5	4	***128***	51	.373	***.495***	***.700***	***1.195***	***218***	374		1	0			*O97/3	MVP-5
1932	37	NYY	AL	133	589	457	120	156	13	5	41	137	2	2	***130***	62	.341	***.489***	.661	1.150	201	302		2	0			*O97/3	MVP-6
1933 ★	38	NYY	AL	137	576	459	97	138	21	3	34	104	4	5	***114***	90	.301	.442	.582	1.023	176	267		2	0			*O97/31	AS
1934 ★	39	NYY	AL	125	471	365	78	105	17	4	22	84	1	3	104	63	.288	.448	.537	.985	160	196		2	0			*O97	AS
1935	40	BSN	NL	28	92	72	13	13	0	0	6	12	0		20	24	.181	.359	.431	.789	119	31	2	0	0			O7/9	
22 Yrs				**2503**	**10622**	**8399**	**2174**	**2873**	**506**	**136**	**714**	**2214**	**123**	**117**	**2062**	**1330**	**.342**	**.474**	***.690***	***1.164***	***206***	**5793**	**2**	**43**	**113**				
162 Game Avg.				**162**	**687**	**544**	**141**	**186**	**33**	**9**	**46**	**143**	**8**		**133**	**86**	**.342**	**.474**	**.690**	**1.164**	**206**	**375**		**3**	**7**				
				G	**PA**	**AB**	**R**	**H**	**2B**	**3B**	**HR**	**RBI**	**SB**	**CS**	**BB**	**SO**	**BA**	**OBP**	**SLG**	**OPS**	**OPS+**	**TB**	**GDP**	**HBP**	**SH**	**SF**	**IBB**	**Pos**	**Awards**
NYY (15 yrs)				**2084**	**9198**	**7217**	**1959**	**2518**	**424**	**106**	**659**	**1978**	**110**	**117**	**1852**	**1122**	**.349**	**.484**	**.711**	**1.195**	**209**	**5131**		**35**	**94**				
BOS (6 yrs)				**391**	**1332**	**1110**	**202**	**342**	**82**	**30**	**49**	**224**	**13**	**0**	**190**	**184**	**.308**	**.413**	**.568**	**.981**	**190**	**631**		**8**	**19**				
BSN (1 yr)				**28**	**92**	**72**	**13**	**13**	**0**	**0**	**6**	**12**	**0**		**20**	**24**	**.181**	**.359**	**.431**	**.789**	**119**	**31**	**2**	**0**	**0**				
AL (21 yrs)				**2475**	**10530**	**8327**	**2161**	**2860**	**506**	**136**	**708**	**2202**	**123**	**117**	**2042**	**1306**	**.343**	**.475**	**.692**	**1.167**	**207**	**5762**			**43**	**113**			
NL (1 yr)				**28**	**92**	**72**	**13**	**13**	**0**	**0**	**6**	**12**	**0**		**20**	**24**	**.181**	**.359**	**.431**	**.789**	**119**	**31**	**2**	**0**	**0**				

Baseball Questions

- How to best measure individual player’s skill, value or performance?
- How fair do trades between teams work out?
- What is the trajectory of player’s performances as they mature and age?
- To what extent does batting performance correlate with the position played?

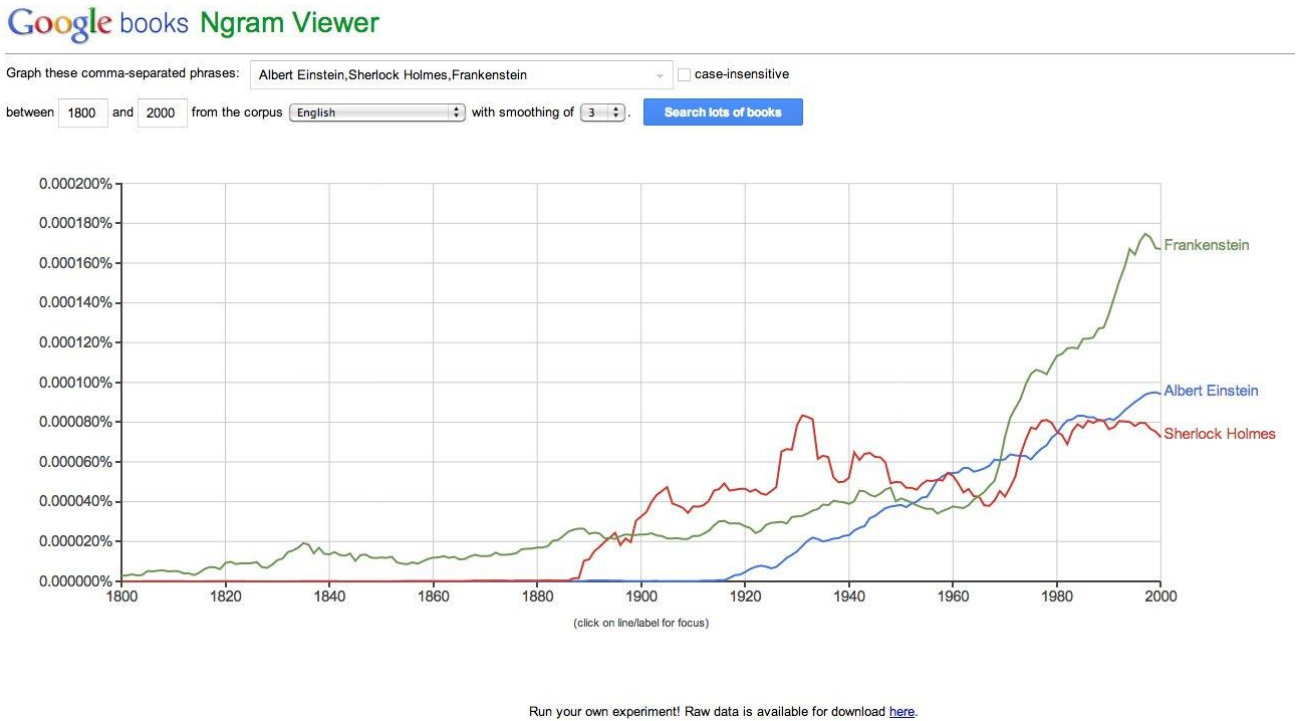
Demographic Questions

- Do left-handed people have shorter lifespans than right-handers?
- How often do people return to where they were born?
- Do player salaries reflect past, present, or future performance?
- Are heights and weights increasing in the population?

Google Ngrams

- Presents an annual time series of the frequency of every “popular” word/phrase with 1 to 5 words occurs in scanned books.
- `Popular’ means appears >40 times in total.
- Google has scanned about 15% of all books ever published, making this resource quite comprehensive.

Google Ngram Viewer



Ngram Questions

- How has the amount of cursing changed over time?
- What is the lifespan of fame and technologies? Is it increasing/decreasing?
- How often do new words emerge? Do they stay in common usage?
- What words are associated with other words, i.e. can you build a language model?

NYC Taxi Cab Data

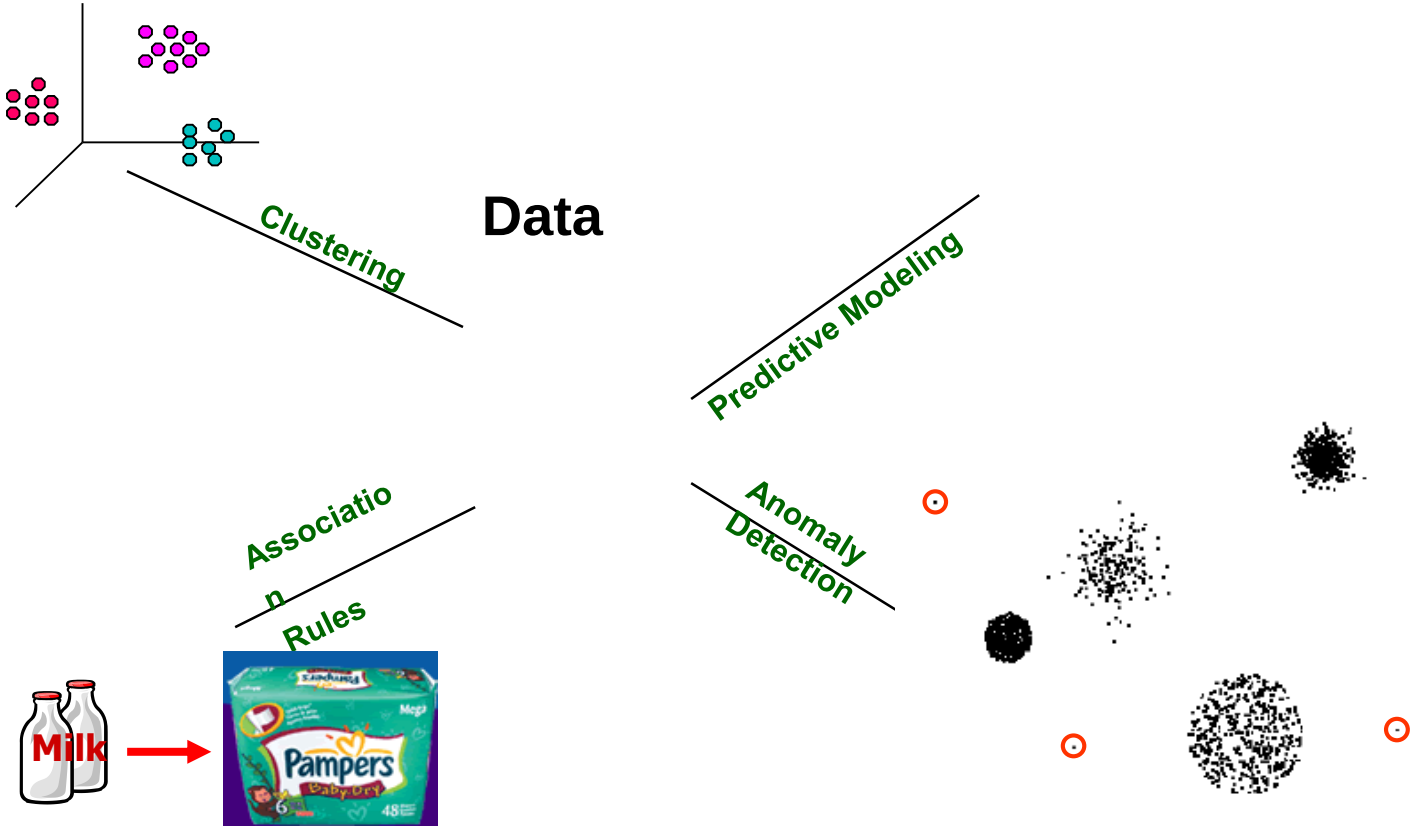
- Gives driver/owner, pickup/dropoff location, and fare data for every taxi trip taken.
- Data obtained from NYC via Freedom of Information Act Request (FOA)

4													
5	Trip data, 2013 ->												
6													
7	medallion	hack_license	vendor_id	rate_code	pickup_datetime	dropoff_datetim	passenger_c	trip_time_	trip_distance	pickup_longitud	pickup_latitude	dropoff_longitude	dropoff_latitude
8	89D227B655E5C82AEC	BA96DE419E7116	CMT	1	1/1/13 15:11	1/1/13 15:18	4	382	1	-73.978165	40.757977	-73.989838	40.751171
9	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1	1/6/13 0:18	1/6/13 0:22	1	259	1.5	-74.006683	40.731781	-73.994499	40.75066
10	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1	1/5/13 18:49	1/5/13 18:54	1	282	1.1	-74.004707	40.73777	-74.009834	40.726002
11	...												
12													
13													
14	Fare data, 2013 ->												
15													
16	medallion	hack_license	vendor_id	pickup_datetime	fare_amount	surcharge	mta_tax	tip_amou	tolls_amount	total_amount			
17	89D227B655E5C82AEC	BA96DE419E7116	CMT	1/1/13 15:11	6.5	0	0.5	0	0	7			
18	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1/6/13 0:18	6	0.5	0.5	0	0	7			
19	0BD7C8F5BA12B88E0B	9FD8F69F0804BD	CMT	1/5/13 18:49	5.5	1	0.5	0	0	7			

Taxicab Questions

- How much do drivers make each night?
- How far do they travel?
- How much slower is traffic during rush hour?
- Where are people traveling to/from at different times of the day?
- Do faster drivers get tipped better?
- Where should drivers go to pick up their next fare?

Machine Learning Tasks …



Predictive Modeling: Classification

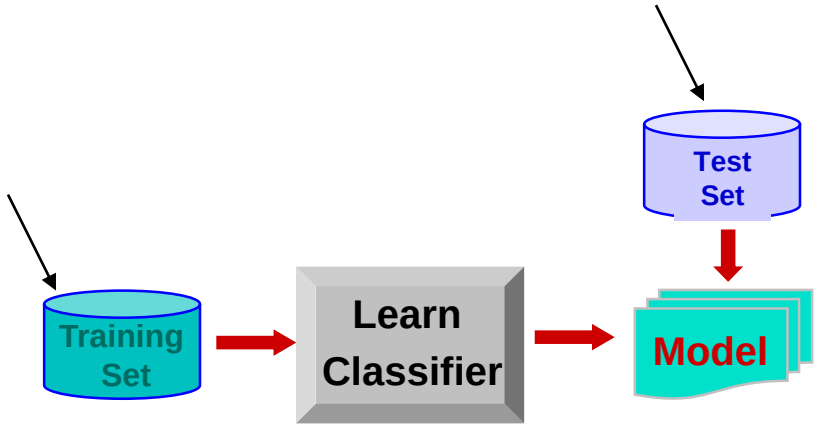
- Find a model for class attribute as a function of the values of other attributes

Model for predicting credit worthiness

Class

Classification Example

categorical categorical quantitative class

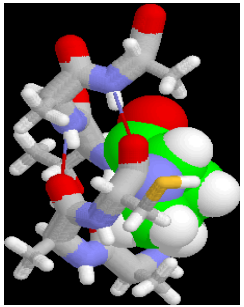


Examples of Classification Task

- Classifying credit card transactions as legitimate or fraudulent

- Classifying land covers (water bodies, urban areas, forests, etc.) using satellite data

- Categorizing news stories as finance, weather, entertainment, sports, etc
- Identifying intruders in the cyberspace
- Predicting tumor cells as benign or malignant



- Classifying secondary structures of protein as alpha-helix, beta-sheet, or random coil

Classification: Application 1

- Fraud Detection
  - **Goal:** Predict fraudulent cases in credit card transactions.
  - **Approach:**
    - Use credit card transactions and the information on its account-holder as attributes.
      - When does a customer buy, what does he buy, how often he pays on time, etc
    - Label past transactions as fraud or fair transactions. This forms the class attribute.
    - Learn a model for the class of the transactions.
    - Use this model to detect fraud by observing credit card transactions on an account.

Classification: Application 2

- Churn prediction for telephone customers
  - **Goal:** To predict whether a customer is likely to be lost to a competitor.
  - **Approach:**
    - Use detailed record of transactions with each of the past and present customers, to find attributes.
      - How often the customer calls, where he calls, what time-of-the day he calls most, his financial status, marital status, etc.
    - Label the customers as loyal or disloyal.
    - Find a model for loyalty.

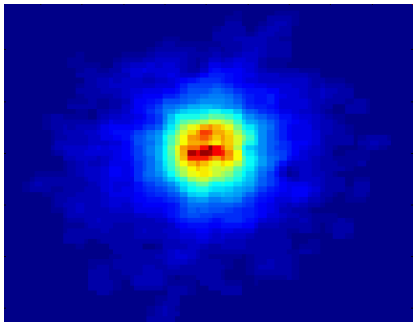
Classification: Application 3

- Sky Survey Cataloging
  - **Goal:** To predict class (star or galaxy) of sky objects, especially visually faint ones, based on the telescopic survey images (from Palomar Observatory).
    - 3000 images with 23,040 x 23,040 pixels per image.
  - **Approach:**
    - Segment the image.
    - Measure image attributes (features) - 40 of them per object.
    - Model the class based on these features.
    - Success Story: Could find 16 new high red-shift quasars, some of the farthest objects that are difficult to find!

Classifying Galaxies

Courtesy: http://aps.umn.edu

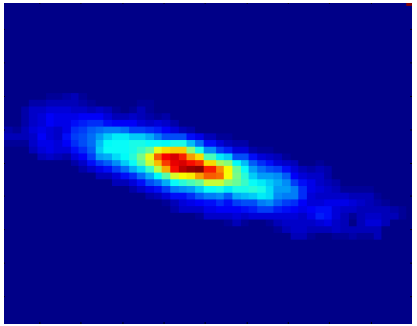
Early



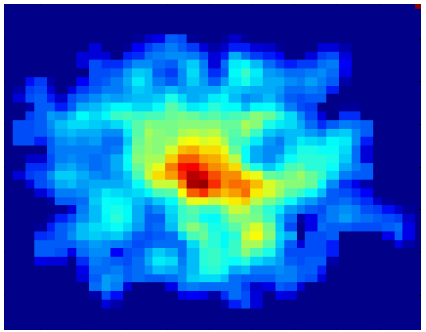
Class:
- **Stages of Formation**

Attributes:
- **Image features,**
- **Characteristics of light waves received, etc.**

Intermediate



Late



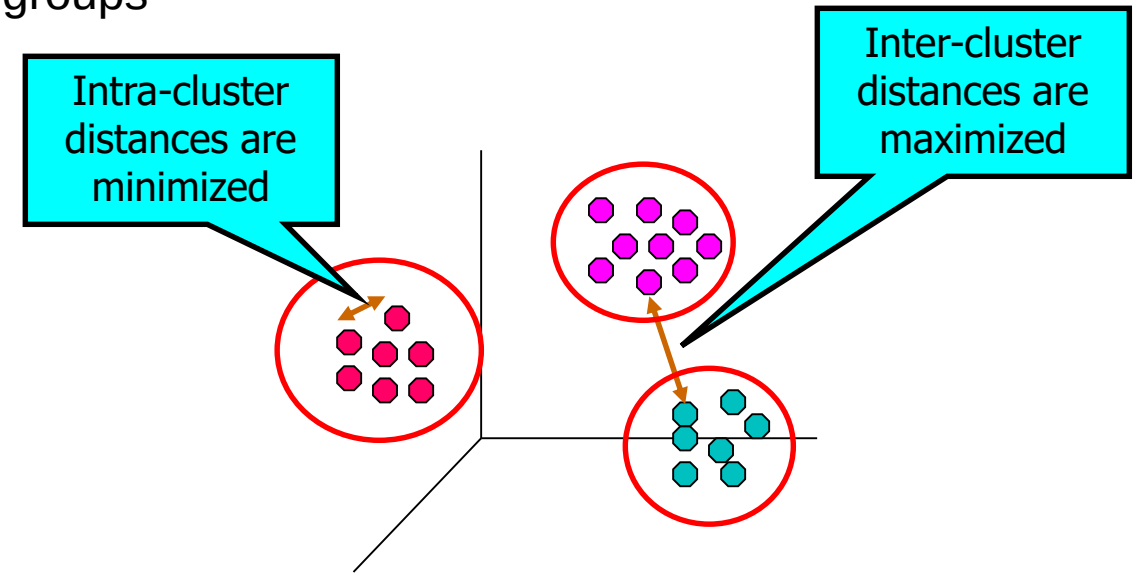
Data Size:
- **72 million stars, 20 million galaxies**
- **Object Catalog: 9 GB**
- **Image Database: 150 GB**

Regression

- Predict a value of a given continuous valued variable based on the values of other variables, assuming a linear or nonlinear model of dependency.
- Extensively studied in statistics, neural network fields.
- Examples:
  - Predicting sales amounts of new product based on advertising expenditure.
  - Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
  - Time series prediction of stock market indices.

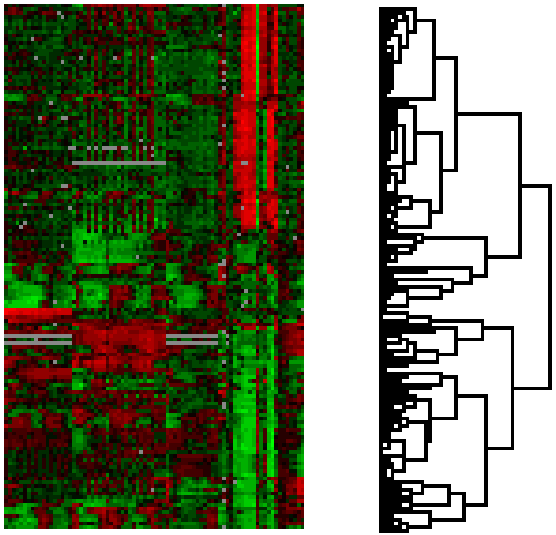
Clustering

- Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups

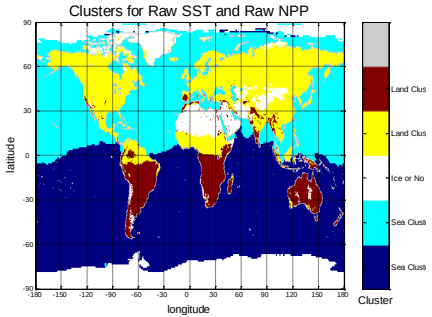


Applications of Cluster Analysis

- **Understanding**
  - Custom profiling for targeted marketing
  - Group related documents for browsing
  - Group genes and proteins that have similar functionality
  - Group stocks with similar price fluctuations
- **Summarization**
  - Reduce the size of large data sets



Courtesy: Michael Eisen



Use of K-means to partition Sea Surface Temperature (SST) and Net Primary Production (NPP) into clusters that reflect the Northern and Southern Hemispheres.

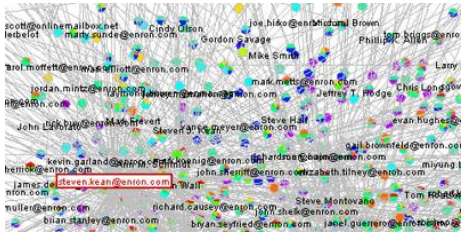
Clustering: Application 1

- Market Segmentation:
  - **Goal:** subdivide a market into distinct subsets of customers where any subset may conceivably be selected as a market target to be reached with a distinct marketing mix.
  - **Approach:**
    - Collect different attributes of customers based on their geographical and lifestyle related information.
    - Find clusters of similar customers.
    - Measure the clustering quality by observing buying patterns of customers in same cluster vs. those from different clusters.

Clustering: Application 2

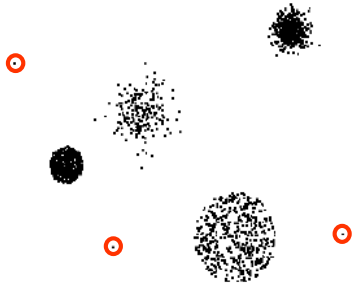
- Document Clustering:
  - **Goal:** To find groups of documents that are similar to each other based on the important terms appearing in them.
  - **Approach:** To identify frequently occurring terms in each document. Form a similarity measure based on the frequencies of different terms. Use it to cluster.

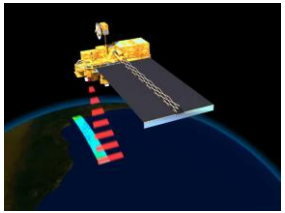
Enron email dataset

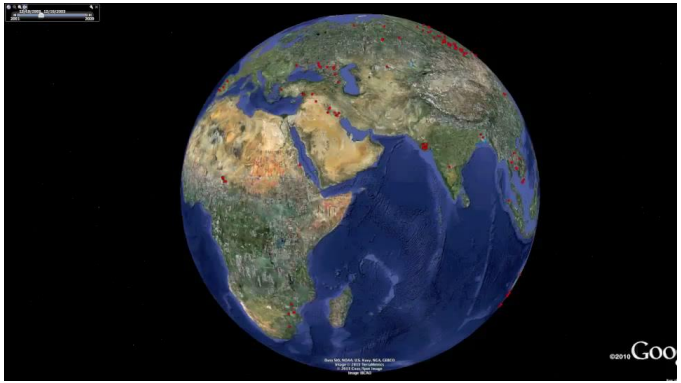


Deviation/Anomaly/Change Detection

- Detect significant deviations from normal behavior
- Applications:
  - Credit Card Fraud Detection
  - Network Intrusion Detection
  - Identify anomalous behavior from sensor networks for monitoring and surveillance.
  - Detecting changes in the global forest cover.







Motivating Challenges

- Scalability
- High Dimensionality
- Heterogeneous and Complex Data
- Data Ownership and Distribution
- Non-traditional Analysis

DS Career path

Introduction

- Graduates of data science program will mostly, and preferably, work as Data Scientists
- Data Scientists can work in any type of organization:
  - Private
  - Governmental
  - Non-for-Profit

Industries

- Any organization can benefit from the data they have, so data scientists can work in any industry:
  - Financial Institutions (E.g., Banks)
  - Government agencies (E.g., Civil Status and Passports Department and Police Department)
  - Healthcare (E.g., Hospitals)
  - Online platforms (E.g., Uber)
  - Large Retailers (E.g., Carrefour and Amazon)
  - Agricultural Companies
  - And much more …

Data Scientist Responsibilities

- Data scientists usually need to build models of verified and validated data sets
- These models will be used by the employer to predict, recommend, or evaluate any future business decision

Data Scientist Responsibilities

- For example, a data scientist, working for a hospital, can build a data model that predicts the best treatment for a specific patient
- The data scientist will use the data that was collected by the hospital about the patients and the treatments that worked and did not work for them in the past.

Data Scientist Responsibilities

- Another example could be a data scientist, working for the police department, can build a data model that predicts the location and time of the next crime before it happens
- The data scientist will use the data that was collected by the police department about the previous crimes to build the proposed model

Data Scientist Responsibilities

- Another example could be a data scientist, working for a large retailer, can build a data model that predicts the demand for certain products and services
- The data scientist will use the data that was collected by the retailer about the previous purchasing transactions
- The data scientist may use data that is provided by external entities

Data Scientist Responsibilities

- Before building the model, data scientist usually need to clean and normalize the data
- Data could be collected from internal sources or/and external sources
- Data scientists need to communicate with data management guys to make sure that necessary data is being collected
  - Data compliance department should be involved to make sure that data collection is properly handled from a legal perspective

More Opportunities

- In addition to working as data scientists, graduates of data science program can work as software development engineers
- In this field, they will mostly specialize in developing platforms that help data scientists in their jobs
- They also can develop dashboards that present business intelligence charts and reports to users

CIS Career path

Introduction

- Graduates of Computer Information Systems (CIS) program can pursue a job in of the following fields:
  - Business Analysis
  - Software Development
  - System Implementation

Introduction

- CIS is an interdisciplinary program that encompasses technology and business courses
- This makes the graduates of this program knowledgeable about how business works and how technology can make businesses more efficient and more effective

Introduction

- People who have knowledge about the technology only will have the following issues while working in the software development field:
  - Difficulty in developing a software that satisfies the business requirements
  - Difficulty in architecting the software systems according to the international standards
  - Difficulty in maintaining existing systems due to lack of knowledge about the business behind them

Example

- CIS program exposes students to healthcare information systems
- When a CIS graduate joins a software development team that is responsible for developing an electronic health record (EHR), he/she will be already aware of the features and functionality of the proposed system

You as a Business Analyst

- You will help customers define their requirements of any proposed software system
- Because you are already aware of how existing systems work, you can make notes and suggestions on how the proposed software system should look like
- Also, It is less likely you will misinterpret the requirements provided by customers

You as a Software Developer

- You will write code to make a software system
- Because you are already aware of how business works, you will be able to choose the right architecture for the system
- The right architecture is one that supports any future improvements without making radical changes to the existing architecture

You as a System Implementer

- You will help users use the software system the right way
- Because you are already aware of how business works, you will be able to provide a very helpful advice on how the software should be used and utilized