Chapter 2. Getting to Know Your Data: Data Description

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Data Science

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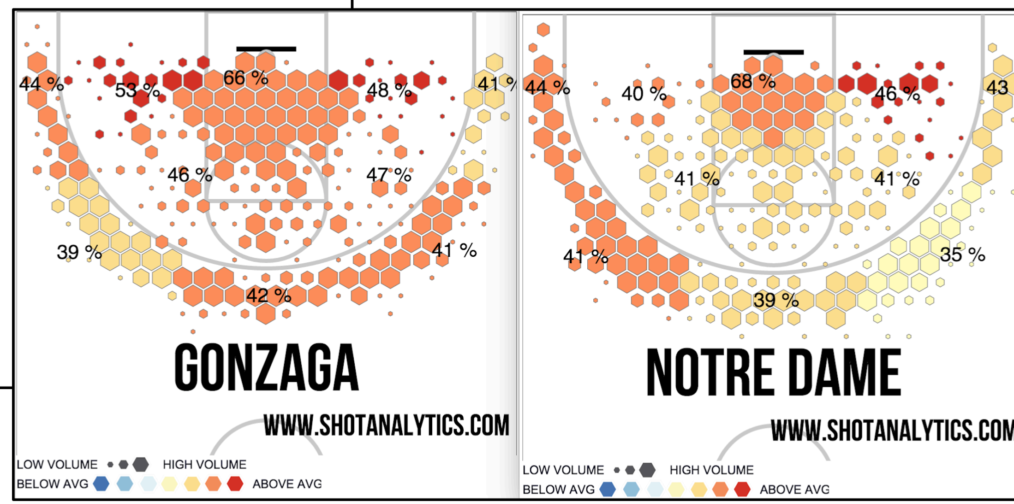
From Data to Knowledge

HOME TEAM: Notre Dame 26-9

			TOT-FG	3-PT		REBOUNDS									
##	Player Name		FG-FGA	FG-FGA	FT-FTA	OF	DE	TOT	PF	TP	A	TO	BLK	S	MIN
03	VJ Beachem..........	f	1-9	0-3	0-0	0	6	6	1	2	3	0	0	1	37
35	Bonzie Colson.......	f	6-13	0-1	6-10	2	5	7	2	18	2	0	2	1	31
00	Rex Pflueger........	g	2-3	0-0	0-0	0	2	2	2	4	0	1	0	0	28
05	Matt Farrell........	g	6-9	3-5	1-3	0	4	4	2	16	4	3	0	2	36
32	Steve Vasturia......	g	3-12	1-2	3-4	3	5	8							
01	Austin Torres.......		0-1	0-0	0-0	1	0	1							
02	TJ Gibbs............		0-1	0-0	2-2	0	2	2							
04	Matt Ryan...........		2-3	0-0	2-2	0	2	2							
23	Martinas Geben......		1-1	0-0	0-0	1	0	1							
	TEAM................					2	1	3							
	Totals..............		21-52	4-11	14-21	9	27	36							

TOTAL FG% 1st Half: 14-30 46.7% 2nd Half: 7-22 31.8%
3-Pt. FG% 1st Half: 2-5 40.0% 2nd Half: 2-6 33.3%
F Throw % 1st Half: 6-8 75.0% 2nd Half: 8-13 61.5%



##	Player	gp-gs	min	avg	fg-fga	fg%	3fg-fga	3fg%	ft-fta	ft%	off	def	tot	avg	pf	dq	a	to	blk	stl	pts	avg
35	Colson,Bonzie	36-36	1156	32.1	236-449	.526	26-60	.433	141-180	.783	104	258	362	10.1	81	0	56	44	50	40	639	17.8
03	Beachem,VJ	36-36	1230	34.2	187-443	.422	87-241	.361	61-73	.836	23	123	146	4.1	46	0	31	40	38	33	522	14.5
05	Farrell,Matt	36-36	1238	34.4	172-384	.448	81-193	.420	81-102	.794	9	63	72	2.0	71	0	196	91	5	51	506	14.1
32	Vasturia,Steve	36-36	1244	34.6	162-374	.433	58-162	.358	91-100	.910	25	116	141	3.9	75	1	119	57	4	42	473	13.1
00	Pflueger,Rex	35-11	750	21.4	59-133	.444	27-68	.397	19-29	.655	18	78	96	2.7	60	0	53	24	12	31	164	4.7
02	Gibbs,TJ	36-1	539	15.0	51-136	.375	17-53	.321	49-59	.831	12	41	53	1.5	49	0	62	28	2	26	168	4.7
04	Ryan,Matt	36-0	286	7.9	43-99	.434	36-83	.434	9-10	.900	6	26	32	0.9	29	0	14	13	1	6	131	3.6
23	Geben,Martinas	34-23	421	12.4	42-65	.646	0-0	.000	23-30	.767	42	73	115	3.4	66	3	25	22	11	13	107	3.1
01	Torres,Austin	36-1	261	7.3	21-38	.553	0-0	.000	6-18	.333	23	31	54	1.5	46	0	7	9	8	9	48	1.3
33	Mooney,John	12-0	46	3.8	5-8	.625	2-4	.500	2-2	1.000	6	13	19	1.6	5	0	2	1	1	1	14	1.2
12	Burns,Elijah	11-0	44	4.0	1-4	.250	0-1	.000	7-8	.875	5	5	10	0.9	5	0	1	2	1	2	9	0.8
34	Mazza,Patrick	4-0	4	1.0	1-2	.500	0-0	.000	0-0	.000	0	1	1	0.3	0	0	0	1	1	0	2	0.5
21	Gregory,Matt	5-0	6	1.2	0-4	.000	0-4	.000	0-0	.000	0	0	0	0.0	0	0	0	0	0	0	0	0.0

Chapter 2. Getting to Know Your Data

- **Data Objects and Attribute Types**
- Basic Statistical Descriptions
- Data Visualization
- Measuring Data Similarity and Dissimilarity

Types of Data Sets: (1) Record Data

- Relational records in relational tables: highly structured
- Transaction data
- Document data: Term-frequency matrix of text documents

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23	Martinas Geben......		1-1	0-0	0-0	1	0	1	1	2	0	1	0	0	2
	TEAM................					2	1	3							
	Totals..............		21-52	4-11	14-21	9	27	36	9	60	10	6	3	4	200

TOTAL FG% 1st Half:	14-30	46.7%	2nd Half:	7-22	31.8%	Game:	40.4%	DEADB
3-Pt. FG% 1st Half:	2-5	40.0%	2nd Half:	2-6	33.3%	Game:	36.4%	REBS
F Throw % 1st Half:	6-8	75.0%	2nd Half:	8-13	61.5%	Game:	66.7%	3

Data Objects

- Data sets are made up of data objects.
- A **data object** represents an entity.
- Examples:
  – Sales database: customers, store items, sales.
  – Medical database: patients, treatments.
  – University database: students, professors, courses.
- Also called *samples*, *examples*, *instances*, *data points*, *objects*, *tuples.*
- Data objects are described by **attributes.**
- Database: (often) rows → data objects; columns → attributes.

Attributes

- **Attribute** (or features, variables)
  - A data field, representing a characteristic or feature of a data object
- Types:
  - Nominal (e.g., red, blue)
  - Binary (e.g., {true, false})
  - Ordinal (e.g., {freshman, sophomore, junior, senior})
  - Numeric: quantitative

Attribute Types

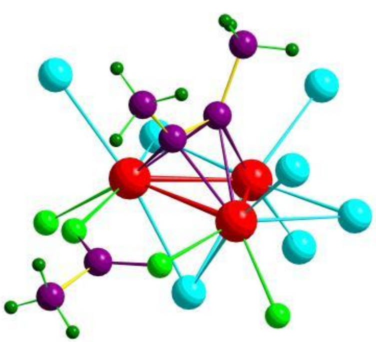
- **Nominal:** categories, states, or "names of things"
  - *Hair_color* = {*black*, *blond*, *brown*, *grey*, *red*, *white*}
  - ________, ________, ________, ________
- **Binary**
  - Nominal attribute with only 2 states (0 and 1)
  - Symmetric binary: both outcomes equally important
    - e.g., ________
  - Asymmetric binary: outcomes not equally important.
    - e.g., ________, ________
- **Ordinal**
  - Values have a meaningful order (ranking) but magnitude between successive values is not known
  - *Size* = {*small*, *medium*, *large*}, ________, ________

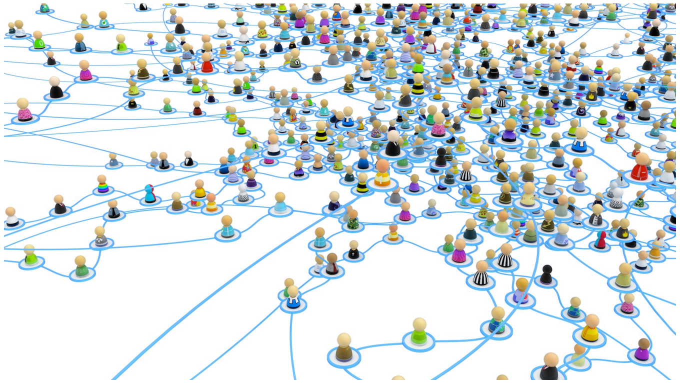
Attribute Types

- **Nominal:** categories, states, or "names of things"
  - *Hair_color* = {*black, blond, brown, grey, red, white*}
  - marital status, occupation, ID numbers, zip codes
- **Binary**
  - Nominal attribute with only 2 states (0 and 1)
  - Symmetric binary: both outcomes equally important
    - e.g., gender
  - Asymmetric binary: outcomes not equally important.
    - e.g., medical test (positive vs. negative)
    - Convention: assign 1 to most important outcome (e.g., HIV positive)
- **Ordinal**
  - Values have a meaningful order (ranking) but magnitude between successive values is not known
  - *Size* = {*small, medium, large*}, grades, army rankings

Types of Data Sets: (2) Graphs and Networks

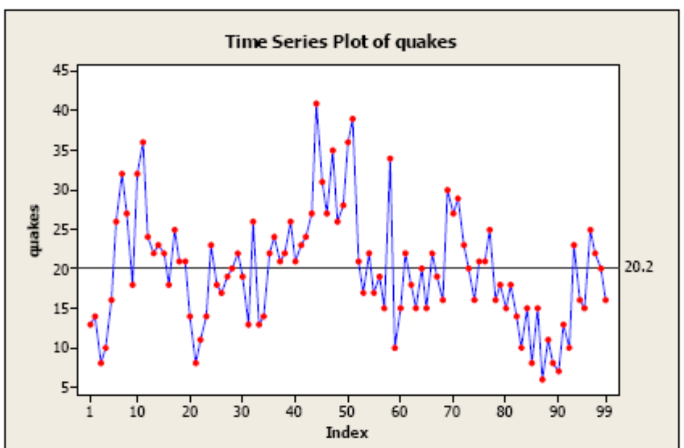
- Transportation networks
- World Wide Web
- Molecular structures
- Social or information networks

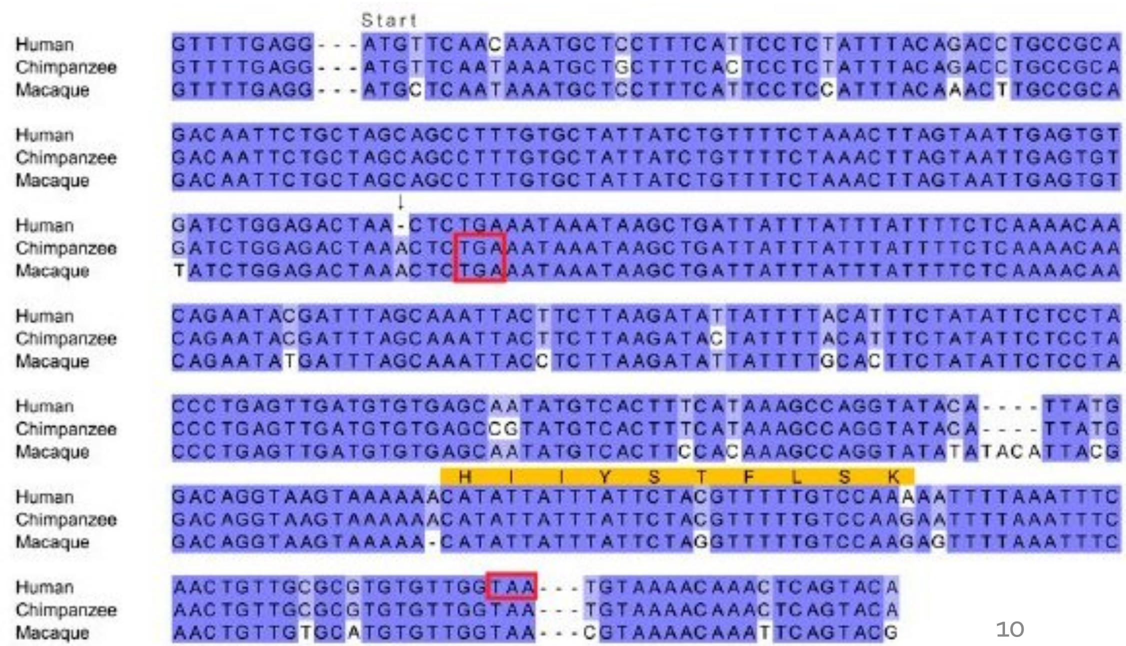




Types of Data Sets: (3) Ordered Data

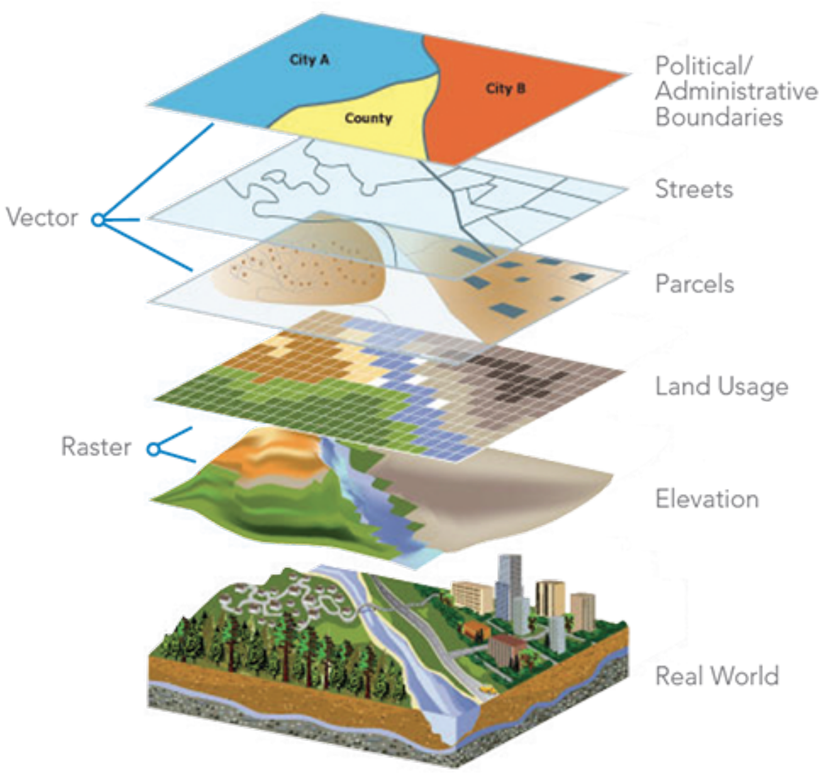
- Video data: sequence of images
- Temporal data: time-series
- Sequential Data: transaction sequences
- Genetic sequence data





Other Types of Data Sets

- Spatial data
- Image and multimedia data



Chapter 2. Getting to Know Your Data

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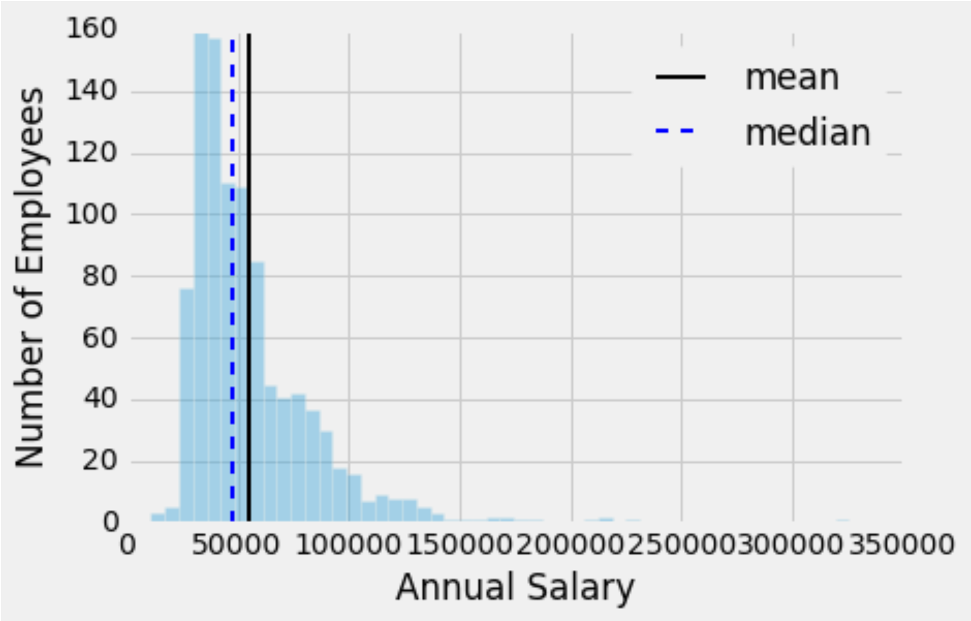
- **Basic Statistical Descriptions**
- Data Visualization
- Measuring Data Similarity and Dissimilarity

Basic Statistical Descriptions of Data

- Motivation: to better understand the data
- Data dispersion characteristics
  - Central tendency: Mean, median, mode, max, min …
  - Outlierness: Variance, standard deviation, Z-score …



Measuring the Central Tendency: (1) Mean and (2) Median

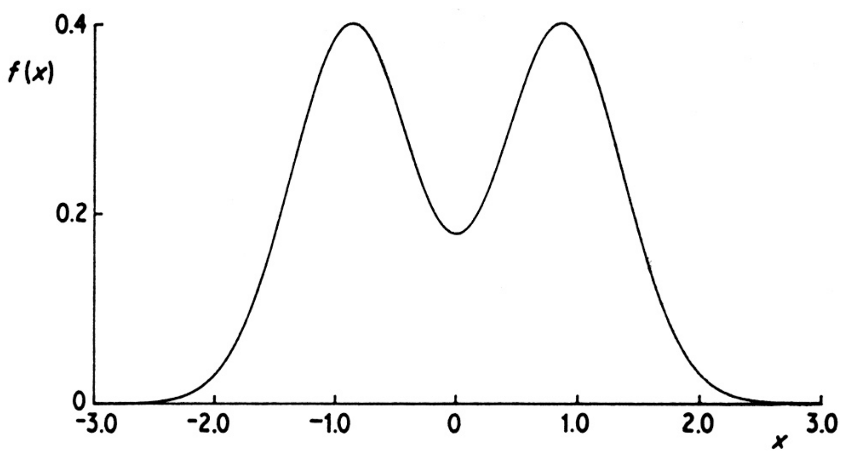
- Mean (sample vs. population):
  - Note: n is **sample** size and N is **population** size.

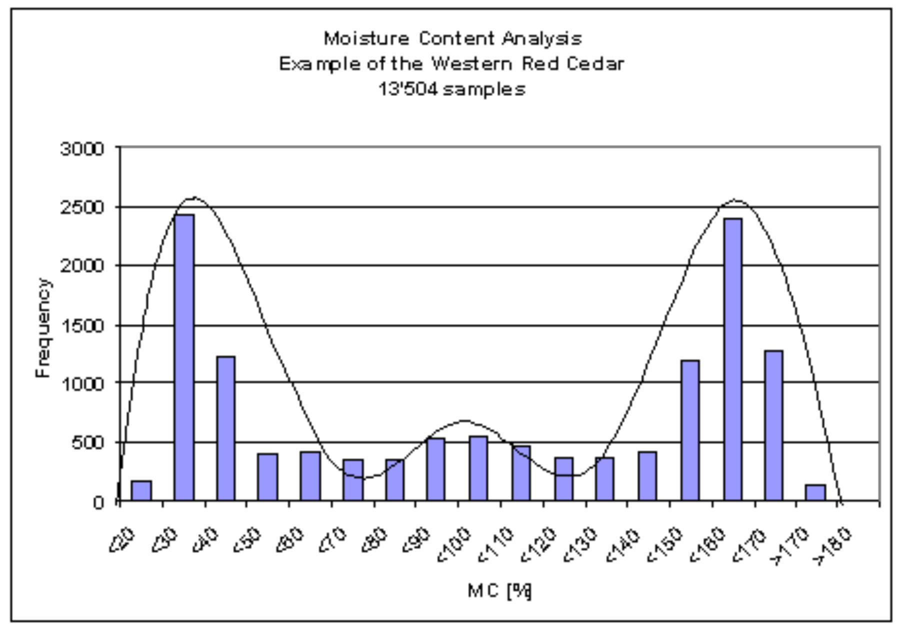
$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad \mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

- Trimmed mean: Chopping extreme values
- Median:
  - Middle value if odd number of values, or average of the middle two values otherwise

Measuring the Central Tendency: (3) Mode

- Mode: Value that occurs most frequently in the data
- Multi-modal
  - Bimodal
  - Trimodal





Measuring the Outlierness: Variance and Standard Deviation

- Variance and standard deviation (sample: s, population: σ)
  - Variance: (algebraic, scalable computation)

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Why?

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \qquad \mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

- Standard deviation s (or σ) is **square root** of variance s^2 (or σ^2)

Biased Sample Variance

$$\begin{aligned}
\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2 &= \frac{1}{n}\sum_{i=1}^{n}\left[(X_i - \mu) + (\mu - \bar{X})\right]^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2 + \frac{2}{n}\sum_{i=1}^{n}(X_i - \mu)(\mu - \bar{X}) + \frac{1}{n}\sum_{i=1}^{n}(\mu - \bar{X})^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2 + 2(\bar{X} - \mu)(\mu - \bar{X}) + (\mu - \bar{X})^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2 - (\mu - \bar{X})^2
\end{aligned}$$

Biased

Unbiased

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$$

Bessel's Correction: 3 alternative proofs of correctness

Measuring the Outlierness: Variance and Standard Deviation

- Variance and standard deviation (sample: s, population: σ)
  - Variance: (algebraic, scalable computation)
    - **Q: Can you compute it incrementally and efficiently?**

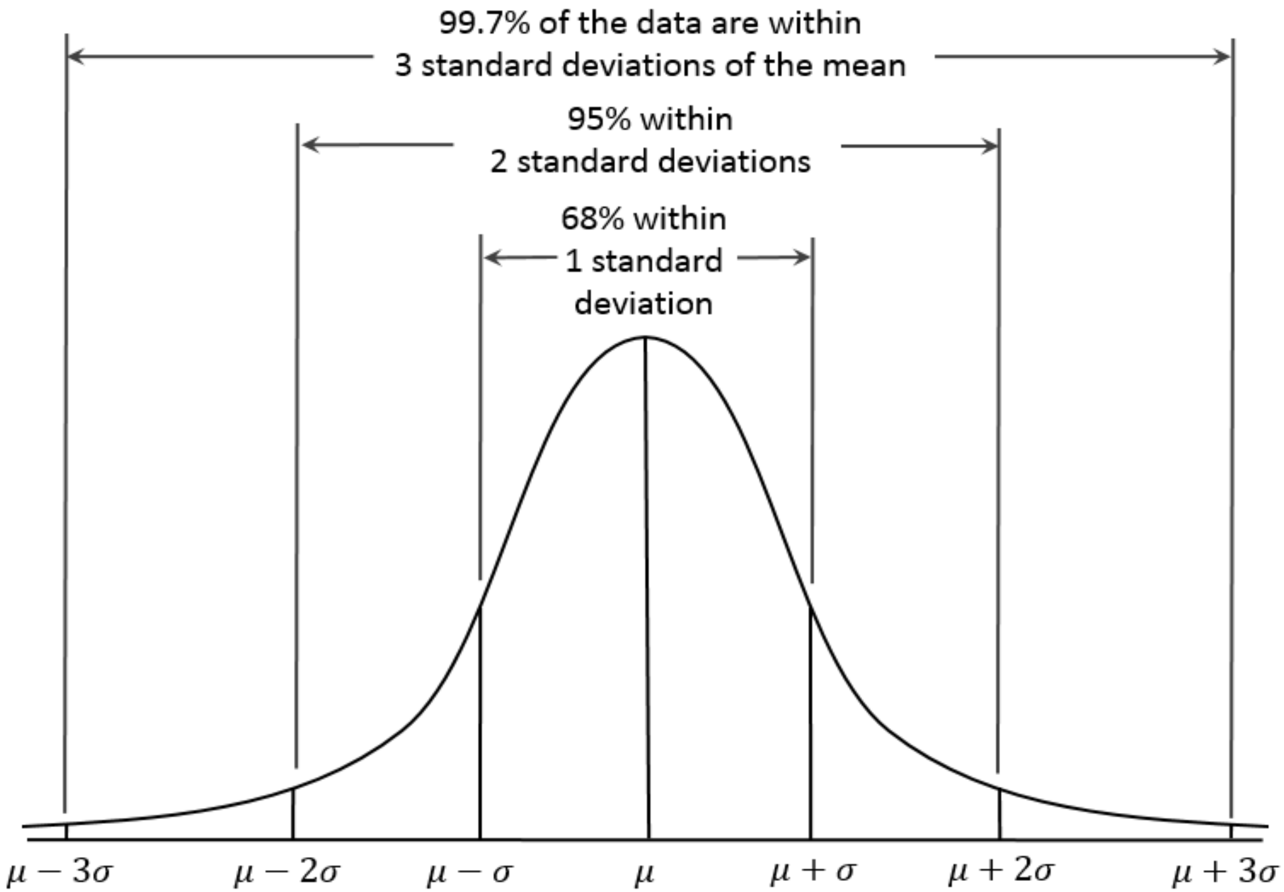
$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \qquad \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \qquad \mu = \frac{1}{N}\sum_{i=1}^{N} x_i$$

- Standard deviation s (or σ) is **square root** of variance s^2 (or σ^2)

Measuring the Outlierness: Properties of Normal Distribution Curve

Z-score: The distance between the raw score and the population mean in the unit of the standard deviation



Z-score -3 -2 -1 0 1 2 3

Z-score Normalization

- The normalized value of X_i is calculated as:

$$Z_i = \frac{X_i - \bar{X}}{s}$$

$$\mathbf{y} = \begin{bmatrix} 35 \\ 36 \\ 46 \\ 68 \\ 70 \end{bmatrix}$$

$$\begin{aligned} s &= \sqrt{\frac{(35-51)^2 + (36-51)^2 + (46-51)^2 + (68-51)^2 + (70-51)^2}{5-1}} \\ &= \frac{1}{2}\sqrt{(-16)^2 + -15^2 + (-5)^2 + 17^2 + 19^2} \\ &= 17\,. \end{aligned}$$

$$\mathbf{z} = \begin{bmatrix} \frac{35-51}{17} \\ \frac{36-51}{17} \\ \frac{46-51}{17} \\ \frac{68-51}{17} \\ \frac{70-51}{17} \end{bmatrix} = \begin{bmatrix} -\frac{16}{17} \\ -\frac{15}{17} \\ -\frac{5}{17} \\ \frac{17}{17} \\ \frac{19}{17} \end{bmatrix} = \begin{bmatrix} -0.9412 \\ -0.8824 \\ -0.2941 \\ 1.0000 \\ 1.1176 \end{bmatrix}$$

vs. Min-Max Normalization:

[0, 1/35, 11/35, 33/35, 1] = [0, 0.0286, 0.3143, 0.9429, 1.0]

Discussion

- Can you use Z-score to automatically find phrases?
  - If we have 1,000 "matrix" and 1,000 "factorization" in 1,000,000 words, and we assume independency, we should have only one "matrix factorization" (expected).
  - But actually we have more! - Outlierness

Jingbo Shang, Jialu Liu, Meng Jiang, Xiang Ren, Clare R Voss, Jiawei Han. "**Automated Phrase Mining from Massive Text Corpora**". Submitted to Transactions on Knowledge and Data Engineering.

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