Who are your best clients? Finding unusually strong buyer-seller links using the power of statistics

Miklós Koren CEU Economics #ceubusinessanalytics

CEU Webinar



CEU highlights

- ► CEU is a world class American university in the heart of Central Europe.
- ▶ One of the most internationally diverse school in the world:
 - ▶ 1,500 students and 300 faculty from 130 countries alumni chapters in 72 countries, representatives in 150 countries
 - All programs accredited in U.S.
- ► Faculty with Ph.D. from elite universities (e.g., Harvard, Yale, MIT, Princeton) and industry experience (e.g., IBM, Epoch, CARD.com, Prezi, Rapidminer).

M.Sc. in Business Analytics

- ▶ 1-year program, accredited in U.S.
 - full time or part time
- Courses in four domains
 - ► Technology: managing data
 - Statistics: analyzing data
 - Economics: interpreting fata
 - Management: acting on data
- Capstone project
 - ► Complete analytics project (solving a business need) at one of our industry partners.
 - Current examples: machine learning based segmentation of tumors in CT scans, residential real estate demand, creditworthiness from payment patterns, optimizing travel costs at scale

Part 1: The power of statistics

Data science

"procedures for analyzing data, techniques for interpreting the results of such procedures, ways of planning the gathering of data to make its analysis easier, more precise or more accurate, and all the machinery and results of (mathematical) statistics which apply to analyzing data." (Tukey,

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A data scientist works with data to make predictions.

"Data died tonight."





I've believed in data for 30 years in politics and data died tonight. I could not have been more wrong about this election.

The power of statistics

Statistics helps us

- 1. discover patterns in data
- 2. quantify trends
- 3. predict the future

Cross Industry Standard Process for Data Mining (CRISP-DM)

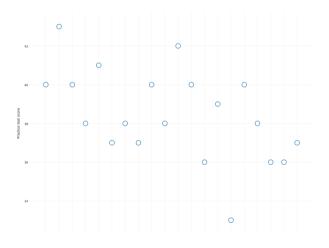
- 1. Business Understanding
- 2. Data Understanding
- 3. Data Preparation
- 4. Modeling
- 5. Evaluation
- 6. Deployment

-

1. Problem

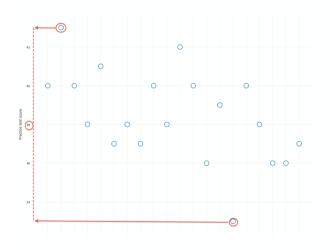
You want to predict your score on a standardized test.

2. Data: Practice Test Scores

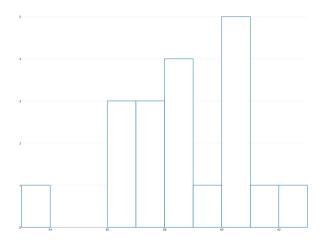


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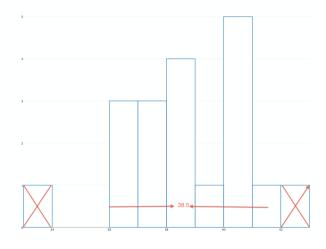
3. One Predictive Model



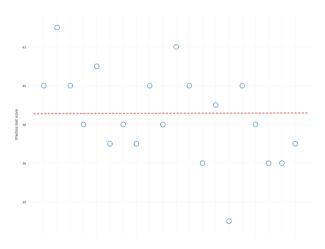
3. The Histogram of Test Scores



3. Another Predictive Model



3. Regression to the Mean



Predict the future

Most statistical predictions are based on the idea that things will look like they did in the past.

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But not all predictions are like that.

North Sea flood of 1953



Predicting extreme values

Notation	$\operatorname{GEV}(\mu, \sigma, \xi)$		
Parameters	$\mu \in \mathbf{R}$ — location, $\sigma > 0$ — scale,		
	$\xi \in \mathbf{R}$ — shape.		
Support	$x \in [\mu - \sigma/\xi, +\infty)$ when $\xi > 0$,		
	$x \in (-\infty, +\infty)$ when $\xi = 0$,		
	$x \in (-\infty, \mu - \sigma/\xi]$ when $\xi < 0$.		
pdf	$\frac{1}{\sigma} t(x)^{\xi+1} e^{-t(x)},$ where		
	$t(x) = \begin{cases} \left(1 + \left(\frac{x-\mu}{\sigma}\right)\xi\right)^{-1/\xi} & \text{if } \xi \neq 0\\ e^{-(x-\mu)/\sigma} & \text{if } \xi = 0 \end{cases}$		
CDF	$e^{-t(x)}$, for $x \in \text{support}$		
Mean	$e^{-t(x)}, \text{ for } \mathbf{x} \in \text{support}$ $\begin{cases} \mu + \sigma \frac{\Gamma(1-\xi)-1}{\xi} & \text{if } \xi \neq 0, \xi < 1, \text{where} \\ \mu + \sigma \gamma & \text{if } \xi = 0, \end{cases} \gamma$		
	$\langle \mu + \sigma \gamma \text{if } \xi = 0, \gamma \rangle$		
	∞ if $\xi \geq 1$,		
	is Euler's constant.		

Predicting extreme values

Potential use cases:

- risk analysis
- ► fraud detection

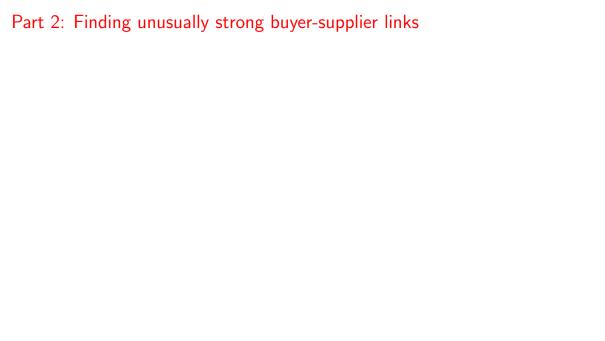
Lessons learned

- 1. Statistics can help discover patterns and make predictions.
- 2. Predictions are as good as past data.
- 3. You can also use statistics to predict the *unprecedented*.

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Questions?



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CRISP-DM

1. Business Understanding: Does each account belong to only one sales rep? Is your sales segmented by region/products?

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- 4. Modeling: What is the statistical model of normal/unusual behavior?
- 5. Evaluation: Evaluate model fit and performance.
- 6. Deployment: What actions will you take? Flag strong links? Follow up with clients, sales reps? Give additional incentives?

Data Preparation

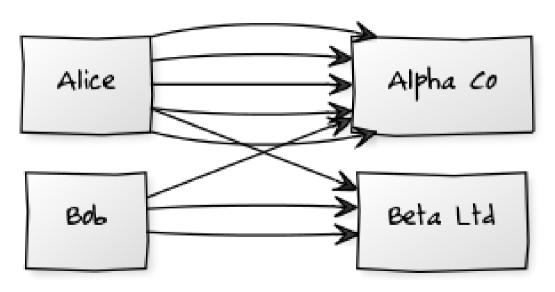
SQL

SELECT sales_rep, buyer, COUNT(contract) AS number_of_contracts FROM crm_table GROUP BY sales_rep, buyer;

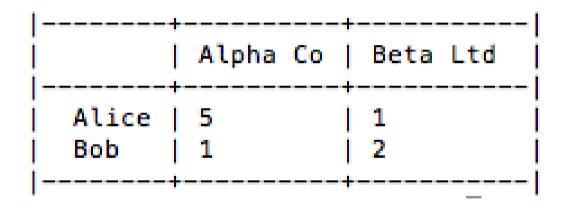
Table representation

	+	number_of_contracts
Alice Bo	lpha Co eta Ltd lpha Co eta Ltd	5 1 1 2

Network representation



Matrix representation



Modeling: What is usual?

▶ We have to model usual link formation.

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- Challenges:
 - "usual" depends on context
 - changing behavior
- ▶ With normative model of "usual," we can quantify value lost to unusual links.

The buyer-supplier sudoku

 	Alpha Co	Beta Ltd	total
Alice Bob total	6	3	6 3 9

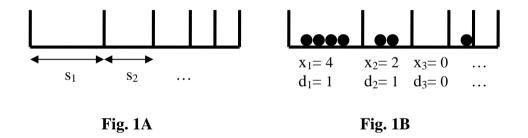
The buyer-supplier sudoku (one solution)

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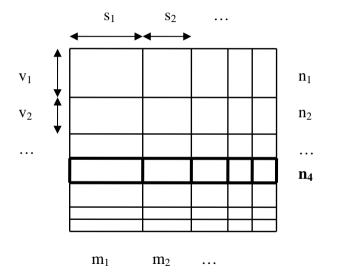
The buyer-supplier sudoku (another solution)

 	Alpha Co	Beta Ltd	+ total
Alice	4	2	6
Bob	2	1	3
total	6	3	9

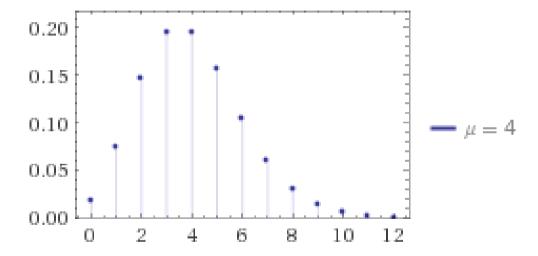
Statistical model: balls falling into bins (Armenter and Koren, 2013)



"Normal" is governed by bin size (Armenter and Koren, 2013)



Under this model, Alice could expect 3-4 contracts from Alpha Co.



Lessons learned

- ▶ Data representation varies by need.
- Even under no preferential association, we expect wide variation in number of contracts.
- Statistical model can predict usual association, deviation can capture special preference.

Questions?



Hungarian procurement contracts

- ▶ We study about 200,000 public procurement contracts of Hungarian governments 1997-2014.
- ▶ Buyer: procuring agency (e.g., municipal government, school)
- Supplier: firm winning conract
- Additional controls: product being procured (Common Procurement Vocabulary), industry of winner, distance, size measures

But first we have to go from this...

Győr Megyei Jogú Város Polgármesteri Hivatal tájékoztatója az eljárás eredményéről (1123)

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1. Az ajánlakérő neve és címe:
Győr Megyel Jogy Város Polgármesteri Hivatal
9021 Győr, Városház ér 1.
Teleforn 99500-115
Fax: 50442-60
Győr-Moson-Sorgom Megyel Bentházási Kft.
9022 Győr, Czuczor G. u. 18/24.
Teleforn 99431-7866
Fax: 90-312-804
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- 2. a) A választott eljárás: hirdetmény közzététele nélküli tárgyalásos eljárás.
- b) Hirdetmény közzététele nelküli tárgyalásos eljárás esetén az eljárás alkalmazásának indokolása: a VII. Kajak-kenu maraton vb időpontja előre kijelölt, és ezen változtatni nem lehet [a Kbt, 70. § d) pontja alapján].
- 3. Az elbírálás időpontja: 1999. február 15.

Ablakcentrum Kft., 9025 Győr, Kossuth I., u. 121.

- Az elbírálás szempontjai: az ajánlatkérő az összességében legelőnyösebb ajánlatot választja. Az elbírálás szempontjainak fontossági sorrendje: vállalási ár,
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- kivitelezes natandeje.
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 Ackleszérezéset szereképítóspan, Kivitészéső Át., 1144 Budapest, Füredi út 74/76.
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Data cleaning

- ▶ Identify buying agencies, contract winners (Entity Resolution).
- ► Remove duplicates.
- ▶ Parse value of contract. (Not used today.)

Sample

- ▶ Contracts in construction, manufacturing and business services.
- ▶ 500 largest buying agencies.
- ▶ 1,000 largest winners.
- ▶ 19,500 contracts.

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- ▶ Contracts in construction, manufacturing and business services.
- ▶ 500 largest buying agencies.
- ▶ 1,000 largest winners.
- ▶ 19,500 contracts.
- ▶ Sparse buyer-supplier network: only 1% of 500,000 potential links exist.

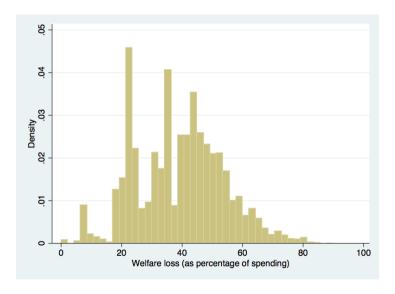
Modeling

ightharpoonup Number of contracts won by i from j follows a Poisson distribution:

$$E(n_{ij}) = \lambda_{ij}$$

 $\lambda_{ij} = F(\text{size}, \text{distance}, \text{purchased product}, \text{political affiliations}, \text{foreign ownership})$

Many agencies spend very inefficiently



Lessons learned

- ▶ Method can be easily applied to transactional data of 200,000 contracts.
- ▶ The buyer-supplier network is very sparse.
- ▶ Losses from misallocating contracts are substantial.

Questions?